Failure prediction using the Hazard model: A study of New Zealand financial institutions

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Marjan Tadayyon Chaharsoughi

Lincoln University

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List of Abbreviations

AMENDED	Amendment in Trust Deed
ANN	Artificial Neural Network
AQ	Asset Quality
AUC	Area under ROC
AUD	Audit Characteristics
AUDITLAG	Number of Days from End of Financial Year to Audit's Sign off Date
AUDREM	Audit Remuneration
BIGN	Auditor Big
BN	Bayesian Network
BOD	Board of Director
BPNN	Back Propagation NN
CA	Capital Adequacy
CA-TA	Current Assets/Total Assets
CBRC	China Banking Regulatory Commission
CSR	Corporate Social Responsibility
DI	Depository Institution
DIRAPPOINT	Number of Directors Appointed through the Financial Year
DIRCHANGE	No Change in Director/s through the Financial Year
DIRCOMP	Director Composition
DIRRESIG	Number of Director Resignations through the Financial Year
DOUBT-GLOAN	Provision for Doubtful Debts less Bad Debts Recovered/Gross Loans and Advances
EARN	Earnings
FI	Financial Institutions
FM	Firm Maturity
GA	Genetic Algorithm
GAAP	Generally Accepted Accounting Principles
GDP	Gross Domestic Product
GLOAN-TA	Gross Loans and Advances/Total Assets
H&L	Hosmer-Lemeshow Test
HPI	House Price Rate
IMF	International Monetary Fund
IMPAIR-TA	Impaired Assets Expense/Total Assets
ISA	International Standards on Auditing
LIQ	Liquidity
AGE	Time in Years from Incorporation Year to Year of Data Collection
LPM	Linear Probability Models
LR	Logistic Regression
M&A	Mergers and acquisitions
MC	Management Competency
MDA	Multiple Discriminant Analysis
MEDIA	Media
MMF	Money Market Fund

MODIFIED	Audit Report Modification
NBDT	Non-Bank Deposit Taker
NBFI	Non-Bank Financial Institution
NETINT-TA	Net Interest Income/Total Assets
NPAT-TA	Net Profit After Tax Before Abnormals/Total Assets
NPAT-TE	Net Profit After Tax Before Abnormals/Total Equity
NUMDIR	Number of Board of Director Members at Year-end
OCF-TA	Net Operating Activity/Total Assets
OCR	Official Cash Rate
OE-OR	Operating Expenses/Operating Revenue
OE-TA	Operating Expenses/Total Assets
OLS	Ordinary Least Squares
OPEC	Organisation of Petroleum Exporting Countries
RELAT-GLOAN	Related Party Lending/Loans and Advances
RELAT-TA	Related Party Lending/Total Assets
ROC	Receiver Operation Curve
RP	Related Party Transactions
RWA	Risk Weighted Asset
S&L	Savings and Loan Association
SIZE	Firm Size
SVM	Support Vector Machines
TA	Total Asset
TA-TL	Total Assets/Total Liabilities
TE-TA	Total Equity/Total Assets
TL-TE	Total Liabilities/Total Equity
TRUSTEE	Trustee
TVC	Time-Varying Covariates
VIF	Variance Inflation Factor

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Abstract

The New Zealand financial markets experienced a horrific loss over a three year period (from 2006 through to 2009). This was due to the non-bank deposit taking sector, which resulted in the failure of over 45 finance companies. This categorical failure resulted in losses over NZ$3 billion, impacting between 150,000 and 200,000 depositors (in a country where total share market capitalisation is approximately NZ$75 billion). This event inevitably raised concern over the quality of financial reports, audits and the role of trustees in the New Zealand financial system.

While several scholars have examined the internal and external factors which caused this financial crisis in an attempt to attribute blame or responsibility, this study investigates the underlining variables that contributed to the financial companies' failure, from three years ahead, to achieve the best prediction model.

The study uses a sample of 35 failed finance companies and covers the period of 2005 – 2009. It compares these companies with the same number of non-failed companies, matched based on asset size. In particular, it studies their financial and non-financial variables for three consecutive years before failure. Logit and hazard models are used in order to identify a suitable model for prediction. The models were developed based on three different variable categories. The first model incorporates only CAMELS financial variables. While the second model uses only Agency-related variables, the third model is expanded to amalgamate both CAMELS financial and non-financial variables.

The study examines the accuracy of the models by testing through out-of-sample data that has been collected from failed financial institutions after 2010, a period characterised by the implementation of new regulations. Error table, AUC, Gini, KS and H measures are used to assess the performance of the models.

The overall results of this study suggest that there is sufficient evidence to support the claim that both financial and non-financial indicators are inferior among failed finance companies when compared to non-failed companies, for three years before failure. The results strongly support the argument that the integration of both groups of variables increases the performance of the model in predicting failure in both the logit model and the hazard model. Therefore, the combined model performs better than the models built solely on financial or non-financial variables.

The study also verifies that the overall accuracy of combined models is more than 85%, with the highest accuracy of 89.70% at three years before failure, in the logit model. Furthermore, the lowest level of false negative and false positive, and the AUC, Gini, KS and H statistics, which measures the discriminant power of the models, show the combined model at three years before failure has the best discriminative power.

Keywords: CAMELS, Corporate Governance, Failure, Financial Institution, Hazard model.

Chapter 1

Introduction

1.1 Background of the Study

Historically, the financial sector in New Zealand has been subject to a notable degree of regulation, especially over the period of the 1930s to the 1980s (Quigley and Reserve Bank of New Zealand, 1992). After the great depression of the 1930s, the New Zealand government took control over a large proportion of economic activity. This included the purchase of several key industries and resources and increased monitoring and restrictions on importing and exporting. Exporters were obliged to sell foreign funds to the Reserve Bank at an exchange rate set by the Minister of Finance; the funds were then sold mainly to domestic producers to pay for imported raw materials. During this time, the government attempted to control the inflation rate through interest rate ceilings, credit guidelines and price controls. However, this approach became less effective over time. The New Zealand economy grew at a respectable rate through government intervention up until 1967. In that time, nearly a third of New Zealand's exports (by value) were concentrated in wool. In June of 1966, wool prices globally dropped by 20 percent; this was followed by further reductions in 1968. These events highlighted serious weaknesses in the New Zealand economy. In addition, the Bretton Wood Agreement, which was anchored by the United States' willingness to convert dollars into gold at the fixed price, came to an end in 1971. This end of the relationship meant that major currencies had to find their values. This event also marked the beginning of rising inflationary pressures in New Zealand that were to persist for the next two decades.

On the 1st of January 1973, the United Kingdom formally entered the European Economic Community. This marked the end of New Zealand's forty years of preferential access to the British agricultural product market under the 1932 Ottawa Agreement. Up until this point, Britain was New Zealand's main export market. This and the creation of Organisation of Petroleum Exporting Countries (OPEC) in the 70s created the desire to establish an independent New Zealand economy.

During the 70s and 80s, the government focused on manipulating the market through interest rate controls, exchange rate controls, subsidies, tariffs and, at times, even freezing market prices, wages and interest rates. In the mid-1980s, public opinion changed. The government was criticised for relying on market manipulations to conquer symptoms of New Zealand's economic disorder, rather than using more general instruments of economic management, to address the underlying causes. This change of opinion saw a change of government. This, in turn, resulted in the implementation of new reforms between 1984 and 1994. These reforms were designed to reduce government interventions in the economy and allowed more freedom for competitive markets to allocate economic resources as they saw fit. Therefore, in the 1980s and 1990s, attention turned toward market methods of sustaining monetary discipline. The Reserve Bank of New Zealand was given independent control of the official cash rate to maintain inflation and new policies prohibited the government from using monetary issues for short-term political gain. Instead, the government was tasked with employing price stability measures that would ensure long-term gain (Dalziel, 2004). These regulations revealed citizen's preferences; to conduct the economy in a way that achieved broader growth, improved economic perspectives and the perception that finance should assist in this process. This reduction in regulations allowed financial institutes more freedom; the interest rate was set by financial institutes in relation to risk factors and banks were able to offer new products (Tripe, 2012).

In July 1984, new measures were instituted to discontinue the interest rate controls forced on various industries as part of the income and price freezes. The credit growth guidelines were removed in August 1984 and the minimum public sector security and mandatory liquid assets holdings (through the reserve asset ratio system), were terminated in February 1985. The result of this freedom was the development of new institutions which provided innovative services which existing institutions were unwilling/ unable to provide. However, this was not all positive; the rapid growth of new institutions meant that regulatory bodies were overwhelmed and struggled to keep up with the changing face of financial services in New Zealand.

Banking system regulations were outlined in the Reserve Bank of New Zealand's May 1987 Bulletin. However, it viewed that the failure of individual institutions should not panic the Reserve Bank unless, in the situation of a general financial crisis which could contribute to the failure of several institutions, this would have a negative impact on the economy as a whole (Tripe, 2012). The other key objective was failure management, as opposed to failure prevention. This was intended to control disturbances caused by failures. This policy was based on the understanding that failure spreads a negative message about market discipline (Doughty, 1986). However, the scope of regulation was largely conservative: in other words, it was believed that the market was the main source of regulation for the New Zealand financial system (Grimes, 1998). This was, however, complemented with a broader legislative framework, which included the Companies Act and Financial Reporting Standards (Tripe, 2012).

Following the introduction of the Securities Act of 1978, banking sector regulations have developed through time. A key development was the bank-specific disclosure regime which came into effect in 1996. This obliges banks to publish a quarterly balance sheet and a year-to-date income statement, along with non-financial information. These disclosures result that the bank's board of directors are individually responsible for signing off the reports. This makes them liable for any misleading or untrue reports.

Although regulations for the banking system have undoubtedly improved since the implementation of the Securities Act in 1978, finance companies have been largely ignored. Regulations for these institutions were still based on the Securities Act 1978 up to 2013. These regulations focused more on form than substance. Finance companies were legally authorised to raise funds from the public as long as they had a trust deed with one of the corporate trustees, and their prospectuses were published every six months, to meet market transparency requirements (Tripe, 2012).

In 2008, New Zealand had nearly 200 non-bank deposit takers (NBDTs) that had NZ$8 billion in retail deposits (RBNZ Staff, 2008b). Significantly, at this time, there was not an official executive body in charge of monitoring these NBDTs. The inefficiency of the regulatory framework for financial institutions was foregrounded by the first wave of NBDTs failures in 2006. The government commenced a review of regulations in the finance sector in September 2005. Some regulatory aspects have not been scrutinised for many years, and many had not been updated in respect of corporate governance codes or international standards. In December 2005, Cabinet formally appointed the Reserve Bank as the single prudential supervision of the NBDTs.

In September 2006, the Reserve Bank published the Discussion Document which highlighted that the existing regulatory framework for NBDTs was insufficient in several aspects. These deficiencies included inconsistencies in regulatory requirements and supervision across different NBDTs, an absence of minimum entry requirements for NBDTs, a lack of governance requirements and insufficient information to enable depositors to assess and compare the risks of depositing with NBDTs.

Although the Reserve Bank was clear about all of the deficiencies, they did not set any specific requirement for financial institution until 2009, after a large number of failures had negatively affected the financial market.

1.2 Statement of Problem

It is the nature of finance companies to fill the gap between the banks and the borrowers when banks cannot, or will not, lend. In New Zealand, finance company clients are higher-risk borrowers and include individuals or unlisted private companies who typically need more credit or more flexibility than what banks can provide them with (often due to their credit history). The number of finance companies, especially non-bank deposit takers, developed rapidly, particularly in the property sector in New Zealand between 2000 and 2007 (Commerce Committee, 2011). Property developers relied on finance companies to cover the gap between what banks could lend them and their funding. As finance institutions tend to lend for riskier projects, and by lower credit security than banks, they charge borrowers higher interest rates. They appeal to investors by offering higher returns on their deposits.

Finance companies' coverage moved to the riskier territory, like financing second-hand cars and consumer purchases, after 2004 when the banks expanded their credit lending into the property sector. Many institutions did not reveal increasing risk levels to investors and tried instead to appeal to investors by offering them higher interest rates. In short, investors did not fully understand the risks that they were taking, by investing money into finance companies. The Reserve Bank confirmed that investment in finance companies rose from $5.1 billion to $7.1 billion during the period of 2004 to 2007 (Commerce Committee, 2011).

As a result of not having an efficient regulatory framework and prudential supervision, the New Zealand market experienced a great loss in the non-bank deposit taking sector, with the failure of over 50 finance companies during the 2006-2009 periods. The first few failures were attributed to a lack of efficient management, as numbers rose, concern was raised about the quality of financial reports, audits and trustees in these finance companies (Allison, 2012). The New Zealand Parliament (Commerce Committee, 2011) inquiry estimated a loss of more than NZ$3 billion, in a country with a total share market capitalisation of only NZ$75 billion. Over 150,000 investors were believed to be affected (Douglas, Lont, and Scott, 2014).

Academic interest has been high in the years following the collapse of the New Zealand financial companies. Several articles have examined both the internal and external factors which are believed to have contributed to this financial crisis, with some seeking to attribute blame (Kabir and Laswad, 2014; Yahanpath and Cavanagh, 2011). Some of the literature questions whether banking regulations in New Zealand are strong and effective enough to protect investors from funds being syphon out of financial institutions by related parties (Tripe, 2012; Wilson, 2009).

There is, however, a lack of studies on how investors could have determined investment risk levels from the disclosed information before bankruptcy occurred.

There is an extensive body of literature on predicting bankruptcy within manufacturing companies (Ak, Dechow, Sun and Wang, 2013; Platt and Platt, 1991) and within financial institutions in countries like Thailand (Jaikengkit, 2004), United States bank holding companies (Avkiran and Cai, 2012) and Turkish commercial banks (Canbas, Cabuk, and Kilic, 2005). Douglas et al. (2014) provide the only study which predicts failure among New Zealand finance companies a year before it happened by using a logistic model. It is important to establish an effective early warning system for predicting bankruptcy, to create better corporate governance and investor confidence (Geng, Bose, and Chen, 2015).

Due to the huge loss that the market experienced from 2005 to 2009, this study's primary aim is to examine a wide range of financial and non-financial variables and highlights the contributed variables in predicting failure, three years before it occurs. This study uses two known logit and hazard models to ascertain which model gives more accurate results for prediction. It will be useful as an effective early warning system for depositors who plan to invest their money in these financial institutions.

1.3 Research Objectives

This study aims to determine the underlining variables that contribute to the failure of financial companies, three years ahead, to assist in the prediction of failure. This study processes all objectives through logit model and hazard model to achieve a better prediction model. The study's objectives are outlined below:

1. To examine whether CAMELS-based ratios can predict failure
2. To examine whether Agency-related information can predict failure
3. To examine whether both CAMELS-based ratios and Agency-related information can predict failure

1.4 Research Questions

The first objective leads us to the first research question.

1. Do failed finance companies have inferior CAMELS-based ratios compare to non-failed companies?

As the Agency-related information is very broad, this study examines specific aspects of that, which are, the board of director composition, related party transaction, audit, trustee characteristics and media. Therefore, the second objective gives rise to the following research questions:

2. Do failed finance companies have adequately different board composition, as opposed to non-failed ones?
3. Do failed finance companies have adequately different related party lending, as opposed to non-failed ones?
4. Do failed finance companies have lower quality audits, as opposed to non-failed ones?
5. Do failed finance companies have adequately different trustee characteristics, as opposed to non-failed ones?
6. Do failed finance companies have adequately different citations in the media, as opposed to non-failed ones?
7. Do failed finance companies have adequately different firm age, as opposed to non-failed one?
8. Do failed finance companies have adequately different Agency-related information, as opposed to non-failed ones?

The last research question covers the third objective:

9. Do failed finance companies have adequately different Agency-related information that improves the ability to predict the probability of failure relative to CAMELS ratio alone?

1.5 Contribution of the Study

This study makes several contributions to knowledge. First, the model by including Size as one of the CAMELS variables and Media as one of the Agency-related indicators, is the most comprehensive and thorough study to date. Second, this study represents the first comprehensive sample observations by using three consecutive year data from the failed finance companies in New Zealand. Third, this study is innovative in its use of the hazard model, a survival model, which provides a robust method to predict the failure of New Zealand finance companies. Fourth, this study expands discriminative power statistics, especially the H measure for model accuracy in failure prediction models in New Zealand. Lastly, by incorporating macroeconomic variables, this study establishes statistical relationships that are robust across different macroeconomic conditions.

1.6 Significance of the Study

In contrast to the banking sector, which operates under strict and clear legislation, New Zealand NBDTs operate under separate unclear legislation. Numerous failures which occurred from 2006 onwards, sent a clear message about the failure of legislation to keep pace with these institutions. These failures were the result of numerous factors; NBDTs disclosure requirements were inadequate, management had the freedom to set their own rules, and there was no government body charged with their oversight. This study should be of immediate benefit to those New Zealand agencies charged with designing a new regulatory framework for this important sector of the New Zealand financial market. Although the New Zealand government has since introduced a prudential regime, there are still some gaps in the current regulatory system that need to be addressed (Yahanpath and Islam, 2014). In addition, this study's results will be useful for auditors engaged in the prediction of bankruptcy. In fact, emerging companies can carefully monitor financial statements and take necessary precautions when interpreting information related to long-term advantages in the competitive market. Further, it will be useful for investors who plan to deposit their money in these finance companies. The results are of potential interest to investors, analysts, lenders, managers and trustees who are concerned with the going concern status of finance companies.

1.7 Chapter Organisation

This study comprises of six chapters. The first chapter, the introduction, has provided an outline of the research to be undertaken, including the background of the study, a statement of the problem, research objectives, research questions and information about the study's significance.

Chapter Two reviews the financial companies and the worldwide regulatory environment, before focusing specifically on New Zealand. Chapter Three provides a review of the literature and findings of prior research, as well as an overview of theories used in this study.

Chapter Four covers the study's research design. It provides specific details on the study's methodology and includes information about the sampling process, data collection methods and measurement of the variables.

Chapter Five reports the findings and analysis of the empirical results. Chapter 6 provides a summary of the study and outlines its key limitations and avenues for future research.

Chapter 2

Financial Institution and Regulatory Environment

2.1 Introduction

Having identified the study's primary goals in Chapter One, this chapter provides an overview of the financial institution, focusing on issues of definition and explanation of the various types of financial institutions in different countries. It offers a summary of the global regulation of financial companies. In particular, it focuses on the financial regulatory environment and in particular, the Basel frameworks (I, II and III). It provides a brief discussion about the implementation of each of the Basel requirements, as well as a critical analysis of them. The chapter also reviews the non-bank deposit taker regime in New Zealand. The final section summarises the most relevant points of the literature review for the current study.

2.2 Financial Institutions

There are many definitions of non-financial banking institutions worldwide. The Directorate-General for Economic and Financial Affairs of Europe defines non-bank financial institutions (NBFI) as:

> *"All financial institutions and quasi-institutions which are principally engaged in financial intermediation by incurring liabilities in forms other than currency, deposits and/or close substitutes for deposits from institutional units other than monetary financial institutions or insurance technical services" (European Union, 2012, P.4)*

The Reserve Bank of New Zealand defines "deposit-takers" as organisations which are not registered as a bank or any other specified group whose main business is lending money or presenting other financial services, like debt securities to the public (The Ministry of Economic Development, 2006)

Non-bank financial intermediation involves the flow of capital from depositors to borrowers. These institutions accept deposits from investors and extend loans and advances to customers and businesses. Borrowers are required to pay interest and the principle which is then used to pay investors (interest and the principal). Therefore, finance companies' main assets include loans, advances and receivables, and interest is the main source of revenue for them (Kabir and Laswad, 2014).

The nature of financial institutions is providing loans in an environment with a higher tolerance for risk than traditional banks. This willingness has allowed them to integrate into New Zealand's financial system by filling a gap where banks are unwilling, or unable to lend (Commerce Committee, 2011). Sometimes the number of parties involved in the process of lending and borrowing may only be a few, like banks, but sometimes a series of institutions are involved. For example, non-bank financial intermediaries (NBFIs) like investment funds (for example, managed funds) invest deposits in other NBFIs (for example, hedge funds) that offer a range of risk-return profiles. Through this chain, borrowers access loans, leases and mortgages, but often through other NBFIs who are involved in lending, rather than banks. As such, non-bank financial institution split the functions of traditional banks across multiple NBFIs.

The majority of NBFIs clients are individuals and small to medium-sized enterprises who are looking for more flexibility or more credit than is traditionally available from the banks. As the nature of finance companies is to lend to riskier clients (due to lower credit security requirements than banks), their interest rates are higher than banks and in turn, they are able to offer investors higher interest rates than traditional banks deposits (Commerce Committee, 2011).

2.3 Types of Financial Institutions

Initially, the banking industry, directly or indirectly, handled all financial services (for example, commercial banking, investment banking, stock investing services, and insurance providers). Collapses in economic and industries in the early 1930s, due to the Great Depression, resulted in the separation of some of these services. The emergence of new financial services, like mutual funds and brokerage funds, during the 1970s and 1980s, resulted in the separation of financial services functions even further (Saunders and Cornett, 2006). By the beginning of the 21st century, regulatory barriers, technology, and financial innovation modifications paved the way for financial institutions to offer a full set of financial services individually. Despite the fact that the financial sector is relatively new, in comparison to other industries, it has grown exponentially (both vertically and horizontally) since the 20th century. This can be seen in the sheer number of the products it offers (Sabri, 2009).

Financial institutions (FIs) serve primarily as financial intermediaries between primary saving and borrowing sectors (Kumar, 2014). Financial institutions like banks, insurance companies, and mutual funds, accomplish the primary function of channelling funds from those with surplus funds (depositors) to those with a shortage of funds (borrowers) (Pilbeam, 2005). For instance, in

2007, although the United States' FIs held over $37.46 trillion worth of assets, their motor vehicle and parts industry, like General Motors and Ford Motor Corporation, held just $0.47 trillion worth of assets (Saunders and Cornett, 2006).

Modern financial systems characterised are made up of a diverse range of financial institutions that offer a variety of financial products. The types of financial institutions differ from one country to another. This study is looking into the financial systems of the three big markets in the world. The financial systems of the United States, Australia and Europe are explained briefly.

2.3.1 The Financial System in the United States

The United States has three major FI groups; Commercial banks, savings institutions, and credit unions (called depository institutions or DIs because a significant proportion of their funds comes from customer deposits). In the United States, commercial banks make up the largest group of depository institutions measured by asset size (Saunders and Cornett, 2006). They manage services similar to those of savings institutions and credit unions; that is, they accept deposits from investors and provide loans to borrowers. They are profit-seeking institutions that perform many functions in a capitalist economy (Kumar, 2014). However, they differ in their composition of assets and liabilities, which are much more varied. Commercial bank liabilities generally contain several forms of non-deposit sources of funds, whereas their loans are broader in range, including consumer, commercial, and real estate loans. Commercial banking activity is also regulated separately from savings institutions and credit unions. Savings institutions, known as thrift institutions, were first created in the early 1800s and consist of savings and loan associations (S&Ls) and savings banks. S&Ls have focused mainly on residential mortgages. They hold individual savings and invest them mainly in mortgages and other securities. The primary purpose of a savings bank is to accept savings deposits (Kumar, 2014). In the United States, credit unions were established in the early 1900s. They are non-profit organisations structured and possessed by their members (depositors). They typically focus on consumer loans financed with member deposits (Saunders and Cornett, 2006).

In the United States, non-depository institutions consist of finance companies, insurance institutions, pension funds, investment banks, and investment companies. The source of funds for finance companies are securities sold to households and businesses, not deposits. These companies obtain funds in the market by issuing their securities, in the form of notes and bonds. They also offer loans like depository institutions.

Insurance companies engage in the dual service of insurance protection and investment. Insurance offered consists of life insurance and casualty and property insurance. The primary source of funds for insurance companies is policy premiums. Insurance companies compete with deposit-taking institutions by providing loans and, with investment companies, in providing investment products. The major use of funds for insurance companies is the purchase of long-term government and corporate securities. Pension funds collect pension contributions from employees and invest the funds in government and corporate securities. Pension funds are normally invested in long-term saving or long-term assets.

Investment banks offer a number of services that include underwriting, leveraged buyouts, treasury funding, venture capital, mergers and acquisitions (M&A), merchant banking, and investment management.

Investment companies are those that pool funds and invest in various types of investments. They are classified as open-ended and close-ended mutual funds. Open-end funds acquire new investments and repay all investments. Close-end funds accept funds only at one time.

2.3.2 The Australian Financial System

The Australian financial system has different types of financial institutions, including building societies, credit unions, money market corporations and finance companies. Building societies initially specialised in offering consumer mortgage loans, but over time have developed into more diversified institutions, with a high concentration on residential mortgages. Some also hold commercial loans, corporate bonds and other investment securities. As building societies focus on long-term residential mortgages and fund them with short-term consumer savings deposits, they are exposed to considerable interest rate risks, which create significant management challenges.

Australian credit unions specialise in short-term consumer loans. As in the US, they are non-profit organisations, and they have rules that limit membership. Money market corporations offer a wide range of financial products, including deposit and lending services. They also provide specialist advice on various financial matters, such as mergers and acquisitions, fundraising and risk management. Additional functions include providing underwriting facilities, trade in financial and exchange markets and funds management. Like the United States, finance companies in Australia do not accept deposits from the public. Instead, they rely on short-term and long term funding from the sale of commercial papers, notes, bonds and stocks and provide loans to both consumers and businesses. Australia has three basic types of finance companies; consumer finance companies which specialise in instalment loans for households, business finance companies which specialise in loans and leases for businesses and sales finance companies who finance the products sold by retail dealers (Kidwell, Brimble, Basu, and Lenten, 2013). In addition to banks and non-bank financial institutions, Australia has insurance companies, superannuation funds and managed funds.

2.3.3 The Euro Zone's Financial System

In the Euro zone, the financial system is divided into a monetary financial institution, like banks, and non-bank financial institutions. The term shadow banking is used for the non-bank financial institution within the Euro zone. In broad term, shadow banking refers to activities related to credit intermediation, and liquidity and maturity transformations that take place outside the regulated banking system (Bakk-Simon et al., 2012)

Non-bank financial institutions in the Euro zone include insurance providers, pension funds and other financial intermediaries. The last group comprises of financial institutions involved in the securitisation of assets, securities and derivatives dealers and specialised financial institutions. Other financial intermediaries include money market funds, private equity firms, hedge funds, and central clearing counterparties. Money market funds (MMFs) are open-ended mutual funds that invest in diversified portfolios of money market instruments, using for a short duration. There are three types of money market funds; 'prime MMF' which invest in money market instruments issued by prime creditors, notably bank deposits and commercial paper. A 'treasury MMF' invests in money market instruments issued by governments. 'Government MMFs' invest in money market instruments issued by government agencies (Bakk-Simon et al., 2012). Private equity firms tend to invest indirectly in companies through private capital markets and companies looking for external finance.

Hedge funds are active investment vehicles that are lightly regulated with great trading flexibility (Fung, Hsieh, Naik, and Ramadorai, 2008). A hedge fund is a fund that can take both long and short positions, use arbitrage, buy and sell undervalued securities, trade options or bonds, and invest in almost any opportunity in any market. The role of central counterparties (CCPs) in financial intermediation is to reduce counterparty risks arising from bilateral transactions over the counter derivatives markets and, in turn, to reduce risks to financial stability stemming from these counterparty risks. CCPs carry out this function by acting as a counterparty to every trade among clearing members, performing multilateral netting and undertaking risk management activities to ensure that the failure of a clearing member does not affect other members (Duffie and Zhu, 2011).

As can be seen by the discussion above, the level of financial development varies from one country to another. It depends mainly on major institutions (banks), and financial market (stock market) developments and practices. Significant differences include the number of banks, the value of deposits granted credit, and owners' equity values. Growth in the financial sector can be seen as a result of the emergence of the non-banking financial institutions, currency systems, financial and monetary policies, a move towards more economic openness, and economic growth itself (Sabri, 2009).

As Sabri notes, each of these financial sectors is regulated by national legal frameworks, which reflects the diversity of the legal bodies and financial mechanisms which exist in the world's economy. It also reflects the degree of maturity in this sector. The types, credits, and mechanisms of any financial sector are generally based on country-specific laws and regulations which organise and consolidate financial activities. For instance, some products and services that belong to the financial sector may be allowed in one economy and not approved in another.

2.4 A Review of the Regulatory Environment for Financial Companies

The rapid growth of the finance sector worldwide has created a need for global regulation. There are few global regulations that govern financial institutions around the world. This section provides a critical discussion of those with most coverage and their impact on host countries' financial environments.

2.4.1 International Regulation

Financial markets and financial institutions play a vital role in today's economies. They function in an environment in which asymmetric information flow is the rule rather than the exception. Financial institutions are responsible for enormous amounts of money. They also run the payments system upon which modern economies depends. The financial sector is also charged with the essential role of allocating financial capital and ensuring it is used productively. In the past, governments have consistently intervened, established regulations and overseen the activities of financial institutions. Financial regulation aims to maintain confidence and promote financial stability (Kumar, 2014). Another motivation is to provide protection for investors against fraud or the dissemination of misleading or inadequate information.

Although there may be benefits in having regulation, it is important to remember there are also significant costs involved in establishing effective regulation. Ideally, from a societal point of view, the marginal benefits from additional regulation should equal or exceed the marginal costs imposed by the regulation. Regulation is not a costless exercise; authorities must devote time and resources to design regulation and ensure compliance as well as costs imposed on firms in meeting the regulations. Further, regulations may distort the conduct of financial business by encouraging financial activities in areas that are favoured by the regulators, rather than those favoured by clients. Regulations may also mean that financial innovation is reduced or presented in a limited form to overcome restrictions imposed by the regulations. A further danger is that overregulation by one financial centre will merely drive business away to less-regulated foreign centres. The degree of regulation and control varies greatly between countries due to different historical, cultural, economic and political factors.

Not only does regulation have a major impact on the operation and development of financial markets, but regulations itself is also often revised and adjusted in response to changing market structures, financial market developments, new financial instruments and the occasional financial scandal or crisis. Unfortunately, because of the uncertainty due to limited information, banks and other depository institutions in the past have been subjected to bank runs, and the financial system as a whole has encountered ‘panics’ (Kidwell et al., 2013). Government intervention in the financial market is usually rationalised on the grounds of ‘market failure’. For instance, during the economic crisis of 2007, liquidity dried up as financial systems failed to recognise specific shocks which generated contagion and other externalities.

2.4.2 Global Regulation of Financial Institutions

The growing internationalisation of finance has meant that international finance is inevitable. Banks and other financial institutions gradually interact with their counterparts in other countries. The failure of the Bankhaus Herstaatt and the Franklin National Bank in 1974 led to an increased interest in prudential supervision at an international level. Many banks have foreign subsidiaries which raise the question of whether a financial institution should follow the home country’s or host country’s regulations has become increasingly important. The following section explains the international financial regulations that are currently in place.

Basel I Framework

In 1988 central bankers from around the world met in Basel, Switzerland. This group of regulators became known as the Basel Committee on Banking Supervision (BCBS). The focus of this initial meeting was on minimum capital requirements for banks which subsequently became known as Basel I, or the 1988 Basel Accord. Basel I was ratified during the 1988 G10 summit and later adopted by over 100 countries. Basel I’s objective was to provide a fair and consistent international banking system that does not rely solely on the regulations of the financial institution’s home or host country as this can provide an inconsistent approach and lead to manipulation. This decreases competitive inequality among international banks and strengthens and stabilises the international banking system, reducing the risk of future shocks.

More specifically, Basel I's aims were to;

1) Create consistency surrounding capital adequacy regulations between banks operating in multiple countries.

2) Allow for capital adequacy standards to be adapted to the risk profile of different banks to ensure stability through the market.

Through the Basel I guidelines a two-tier system has been created to define capital:

The first tier, "Tier I", is known as Core Capital and consists mainly of share or stock issues (shareholders' equity) and requires reserves to be set aside to protect against future losses, for example "loan loss reserves". This also acts to smooth out income variations and, for the banks, minority interests in consolidated subsidiaries.

The second tier, "Tier II", is known as Supplementary Capital and is compiled through all other capital, which includes, but is not limited to, gains on investment assets, long-term debt (where the maturity date exceeds five years), gains on investments and hidden reserves (over estimates for bad debts on loans and leases).

Basel I uses the Risk Weighted Asset (RWA) to measure bank risk levels. RWA provides a bank assets weighting, in respect to the relative risk associated with the particular class of asset. This ensures that the bank retains stability as assets are written off during the normal course of business. Basel I states that a minimum of 8% regulatory capital reserve must be held by each bank (defined in relation to the bank's RWA).

Basel I divides credit risk into three distinct categories:

1. On-balance sheet risk
2. Trading off-balance sheet risk which comprises of derivatives, including, but not limited to, currency derivatives, interest rate derivatives, commodities, and equity derivatives
3. Non-trading off-balance sheet risks, which is comprised of general guarantees; these include forward purchase contracts and transaction-related debt assets

The Basel Accord was the first attempt to create a uniform system of global regulations. While it represented a massive step forward, it was not without issues. As outlined below, multiple aspects of the Basel I framework have been criticised:

- Differentiation within the credit risk is not wide enough to prevent failure. The establishment of a minimum capital ratio of 8% is insufficient to prevent the failure of large banks. This also does not account for changes in the nature of default risk.

- Credit Risk for the bank changes depending on the terms of the credit exposure (the maturity date). Basel I failed to take this into consideration. Therefore, the capital requirements were unaffected by the maturity of the credit exposure.
- Different countries experience different levels of risk in relation to their exchange rates and their economies, not to mention political factors. However, this has not been considered in the Basel I Accord.
- While the Basel I accord has addressed capital adequacy issues within the international banking system, it has however failed to consider the liquidity of this capital. A lack of liquidity within these capital reserves allows for potential exposure to failure within the international banking system.

Through Basel I, banks were able to manipulate the Capital Adequacy requirements. Major banks began to sell off certain assets that were considered high risk under Basel I. This would allow them to improve their capital adequacy ratios (for example, credit card book). This process was known as “regulatory arbitrage”. This resulted in the banks within three countries (the UK, the USA and Germany) artificially increasing their capital ratios well above the 8% required under Basel I (12-13% during 2003).

The Basel II Framework

The limitations of Basel I, as expressed above, prompted action. The Basel II accord maintained the minimum requirement of 8% capital based on RWA. The focus was on establishing a minimum level of capital reserves for internationally active banks. This was emphasised as the minimum level of capital required internationally by banks. However, governments retained the ability to set higher capital requirements within their borders. A major step forward in the Basel II framework was the addition of a supervisory review process and market disciplines. The Basel II framework is divided into three distinct sections, known as the three pillars;

- Minimum capital requirements
- Supervisory review process
- Market discipline

Figure 2.1 provides a summary of Basel II’s pillars. The first pillar deals with the calculation of total minimum capital requirements for credit, market, and operational risks.

Pillar I: Minimum Capital Requirements	Pillar II: Supervisory Review Process	Pillar III: Market Discipline
Capital requirements for credit risk - Standardised approach - Foundation IRB approach - Advanced IRB approach **Market risk** - Standardised approach - Internal Value at Risk models **Operational risk** - Basic indicator approach - (Alternative) Standardised approach - Advanced measurement approach	**Regulatory framework for banks** - Internal capital adequacy assessment process (ICAAP) **Supervisory framework** - Evaluation of internal systems of banks - Assessment of risk profile - Review of compliance with all regulations - Supervisory measures	**Disclosure requirements of banks** - Transparency for market participants concerning the bank's risk position (Scope of application, risk management, detailed information on own funds) - Enhanced comparability of banks

Figure 2-1 Summary of Basel ll Pillars

First Pillar: Minimum Capital Requirements

Under the first pillar, there are two methods of calculating capital requirements based on credit risk. These methods are known as the standardised approach for credit risk and the internal rates-based (IRB) approach.

Under the standardised based approach credit risk is weighed in terms of the types of claims, external credit assessment institutes (for example, Standard and Poor's, Moody's and Fitch, approved by the RBNZ), and implementation considerations. Under the Standardised approach lending to a company with an AAA credit rating would carry lower credit risk, compared to lending to a company with a lower risk.

Under the internal rating-based (IRB) approach banks are able to implement their internal review of the risks associated with different categories of capital requirements, based on their exposure. This is subject to approval from the regulatory supervisor (the RBNZ for New Zealand), as well as other minimum disclosure requirements and other conditions suggested by the Basel Committee. The IRB approach is further divided into the "Foundation IRB" and the "Advanced IRB", with banks were given the option of selecting either approach. To ensure consistency and allow for comparisons and audits by regulators, banks using the IRB approaches are still required to complete the standardised approach, thus allowing for further scrutiny.

The Market Risk component of the first pillar is concerned with changes to external market conditions, such as exchange rate variances, interest rate variances and changes to commodity prices. Market risk can also be associated with the external market based financial risks. Again, there are two approaches used to determine the Market Risk. These two methods are known as the standardised approach and the internal model.

Under the standard approach determining market risk involves equity positions, derivatives and interest rate risks. Two separately calculated charges are used to express the minimum capital requirement. The first capital charge relates to modelling specific risks; this seeks to protect against movements in individual security prices due to factors relating to a specific issuer. The second capital charge relates to general market risk. This identifies changes in the market that result in increased risks of loss.

Operational risk, in relation to the first pillar of Basel II, is the risk of loss resulting from physical damage, people, systems, legal risks, inadequate or failed internal processes and from external events. However reputational and strategic risk was excluded from this definition. Basel II banks choose between three distinct methodologies to calculate their capital requirements under operational risk.

1. The Basic indicator approach is based on an individual bank's average revenue from the three previous years.
2. The Alternative standardised approach is based on the annual revenue of each line of business within the financial institute.
3. The Advanced measurement approach is based on an internally developed empirical model to calculate the capital requirement for operational risk.

Second Pillar: Supervisory Review Process

The second pillar is focused on the supervisory review process or the key principals which revolve around, risk management, transparency and accountability around banking risks. On an operational level, guidance is provided in relation to operation risk, securitisation, credit risk, interest rate risk and cross-border communication and cooperation. Basel II's supervisory review process ensures that banks must retain adequate capital reserves to meet the risks associated with their business.

The supervisory review process ensures banks develop better risk management techniques and enables them to better manage and monitor their risks. This process also recognises that banks' management teams have a responsibility to develop internal assessment processes to ensure that their capital targets correlate with their individual bank's risk profile.

This supervisory review process can be categorised into four key principals, which encompass business risk, strategic risk, systematic risk, interest rate risk, and external factors. The four key principles developed under the supervisory review process are outlined below:

- Principle 1: An internal process needs to be developed by the bank to assess their overall capital adequacy based on the bank's risk profile. A strategy needs to be developed to maintain capital adequacy levels. This process needs to be rigorously stress tested to ensure that it can identify changes in market conditions and or possible events in the future that could impact on the bank.
- Principle 2: Supervising authorities need to regularly check in with banks to review their internal capital adequacy assessments, and ensure that are complying with Basel regulations and capital ratios
- Principle 3: Banks are expected to operate above the minimum regulatory capital ratios. Supervising authorities must have the ability to force banks to hold excess levels of capital, over and above the minimum required.
- Principle 4: Supervisors need to act immediately to prevent banks from allowing capital to fall below minimum levels. Supervisors need to be willing and able to act immediately to ensure that any situation is remedied and action is taken if the bank continues to operate outside regulations.

Above all, the supervisory review process needs to ensure transparency and accountability, to guarantee accurate monitoring of capital ratios and cross-border communication. The Basel committee has also identified specific issues related to credit risk, lending book risk, operational market risk and interest rate risk to be addressed by supervisors.

Third Pillar: Market Disclosure

Market Discipline is an integral part of the banking system as it allows shareholders and stakeholders to make informed decisions about the bank's risk position. Market Discipline is the process whereby stakeholders access information to effectively monitor banks' decisions to ensure that they are acting in the best interest of their stakeholders. Basel II promotes market discipline by developing detailed disclosure requirements to allow stakeholders to obtain information on risk exposure, risk assessments, capital, and scope of application and the capital adequacy of the organisation. For market discipline to operate efficiently, it is important that stakeholders receive information in a timely fashion. It also needs to be accurate and meaningful information. This allows stakeholders to make informed decisions about the bank's operations and risk exposure. Basel II requires mandatory disclosure.

Basel II Failures

Like Basel I, Basel II was characterised by numerous shortcomings. The implementation of Basel II was not successful by any stretch of the imagination as it coincided with the global financial crisis which began in the last quarter of 2007. In the European Union, Basel II regulations were implemented in 2007. In the United States, the implementation of Basel II regulations was only required for the largest banks; this was because the United States government determined that the Basel II accord was designed for internationally active banks. However, under the European Union, Basel II was implemented across all EU banks, regardless of their size or whether were considered internationally active or not. China and India opted not to implement Basel II requirements as they felt that Basel II did not address the risks that were uniquely associated with their markets.

Another major failing of the Basel II framework was the internal rating based approach, which allowed banks to use their risk models to set minimum capital levels. This feature limited Basel II's effectiveness. Banks underestimated their risk exposure by using the internal rating based approach, leading to a reassessment of their credit risk. Basel II also failed to address undercapitalisation within the banking system. This lead to insolvency in several banks, as the extent of losses within the subprime mortgage market began to materialise. Under Basel II banks used their own forms of risk assessment and were able to determine the level of risk their off-balance sheet vehicles carried or not. This meant that banks were allowed to determine which risks they should be accountable for.

Basel II's approach to risk management was not comprehensive and did not fully detail market risk, securitisation or trading book. Under Basel II, banks tended to calculate their capital requirements through market risk models. Examples include the Value-at-Risk model, which contributed to the collapse of the subprime mortgage market, through systematically underestimating the market risk. Banks took excessive risks while not fully realising that they had insufficient capital in place to cover their exposure. As previously mentioned, the Basel II framework also failed to address liquidity and leverage risks within the banking sector.

For all banks, there are costs associated with holding capital aside to meet regulatory requirements. This capital is unavailable, meaning it cannot be invested in assets which would generate a higher rate of return for the bank (for example, lending facilities). As a result, large banks often manipulated their position to meet Basel II regulations. Basel II failed to put adequate regulations in place to prevent banks from manipulating capital positions in this way.

Due to the pro-cyclical nature of Basel II, a common suggestion is that banks should be required to hold higher capital reserves. During an economic boom, market risk models are perceived to hold a lower risk to banks; therefore banks are able to reduce levels of regulatory capital. Banks are then able to invest this capital into assets that generate a higher rate of return, such as lending products. However, when the cycle turns downward, banks are exposed, with lower levels of regulatory capital. This prompts banks to freeze lending facilities in an attempt to increase their capital reserves, causing a ripple effect in the wider economy.

The Basel III Framework

Basel III builds on the framework established by the Basel I and Basel II accords. Basel III was developed by the Basel Committee in 2010 in response to the 2007/8 global financial crisis and the limitations of Basel II. Basel III was meant to be implemented by 2015. However, amendments made by the Basel committee in 2013, extended full implementation until 2019. Amendments included broader definitions of liquid assets. The Basel committee's primary goal was to strengthen the banking sectors' resilience by building on the Basel I and II frameworks. This would create a disincentive for banks to generate excessive leverage on and off balance sheet, which was a major contributing factor to the severity of the global financial crisis.

The basic summary of the proposed changes under Basel III (2010) are as follows:

- **(First)** **Increase the quality, consistency, transparency and the level of the capital base.** Basel III's first recommendation is to focus on increasing the quality of capital. This will be achieved by using a two-tier capital system, with common shares and retained earnings forming Tier 1 capital and supplementary capital and other categorises forming Tier 2 capital. Increasing the level of regulatory capital to be held by the banks will improve the banking sector's loss-absorption capacity.
- **(Second)** **Introduction of a leverage ratio.** The leverage ratio will be introduced under Basel III, to provide a backstop. The leverage tool is designed to ensure that banking institutes do not build up an excessive amount of leverage, as this contributed to the global financial crisis. The leverage will be non-risk-sensitive to reduce the procyclical flaw in Base II.
- **(Third)** **Short term liquidity to be increased.** An increase in short liquidity coverage ratios will be supported by longer term liquidity ratios.
- **(Fourth)** **Develop balance sheet funding from stable long term sources.** As noted above, short term liquidity is important. However, this needs to be

reinforced by longer term equity (known as the net stable funding ratio). This will encourage banks to seek stable sources of long term funding and move away from short term funding models.

(Fifth) **Risk cover ratio to be strengthened.** Counterparty Credit Risk exposure was a major flaw in the Basel II framework. Basel III aims to adjust financial institutes and counterparty influence arising from banks' derivatives and secure financing.

Basel III has effectively tripled the regulatory capital reserves that international banks need to hold. Under Basel III, core capital has increased to 4.5% of RWA's (up from 2%), with a concomitant increase in liquidity ratios (up 2.5%). National regulators have been provided with a discretionary counter-cyclical buffer of 0% to 2.5% which can be applied in times of high credit growth.

The cyclical nature of the market has been an issue for previous Basel models. The changes to capital requirements, liquidity and leverage ratios, are designed to increase regulatory capital buffers to minimise and eliminate adverse shocks.

The Impact of Basel III Implementation

Under the new Basel III capital requirements, more focus is given to tier 1 capital, which is predominantly made up of common shares and retained earnings. Banks will be unable to rely as heavily on loss-absorbing assets, such as investments in unconsolidated subsidiaries, minority interest and goodwill. Hence, the more rigid treatment of underlying capital makes up the capital requirements. It is believed that this will have a positive effect by providing a 3-4 times increase to the market risk capital requirements for large, internationally active banks.

Basel Reforms: A Critical Analysis

Like the previous frameworks, Basel III has not escaped criticism. Firstly, the requirements for banks to change how regulatory capital reserves are calculated, and the increased minimum levels, have a real economic cost. Although this may reduce bank risk-taking behaviour, it also represents capital that must be held in reserves and is therefore not available to be used for investment in assets generating a higher rate or return, to be paid as a dividend to shareholders, or to finance a new project.

Although the classification of capital has been tightened under the Basel III framework, banks still retain the ability to determine their credit risk using internal based models. Currently independent standard does not exist which allow banks to review their risk assumptions or assertions. This inevitably impacts regulators' abilities to review bank risk assumptions.

2.5 New Zealand Financial Companies

In New Zealand, non-bank financial institutions are generally known as non-bank deposit takers (NBDTs).

NBDTs are vital to New Zealand because of their large contribution to the economy, both in terms of funding and employment. Although non-bank financial institutions in New Zealand hold only 4.9% of the total financial system's assets, they lend on the property, agriculture, non-residential and consumer sector, residential mortgage and other businesses (RBNZ, May 2010). Thus, problems in this sector could affect other sectors and potentially New Zealand's economy.

The New Zealand's property sector has rapidly expanded over a ten-year period (1997 – 2007). This has occurred alongside the rise of various finance companies (KPMG, 2007). Many of the property developments during this period relied on finance companies for "mezzanine" funding to bridge the gap between what banks would lend with the security of a first mortgage, and the developer's own funding from equity or pre-sales. As a finance company's security usually ranks below that of the bank, it generally carries higher lending risks.

Another important trend over this period was the expansion of banks' own lending in the property sector. As banks' appetites for credit expanded, finance companies were forced to collaborate with riskier lenders. In addition, finance companies were involved in an enormous expansion of credit, financing second-hand cars and other consumer purchases, with little oversight on the capacity of individual borrowers to repay their loans. While the increased risk should have meant a corresponding increase in the returns finance companies offered investors, they did not always do so. Some of them sought to minimise the perceived risk differences between themselves and the banks by offering only slightly higher interest rates to depositors. At the same time, they actively marketed themselves among retail investors, like households. According to Reserve Bank of New Zealand data, between December 2004 and June 2007, household investment in finance companies rose from $5.1 billion to $7.1 billion, an increase of 39% (Commerce Committee, 2011).

2.6 Non-Bank Deposit Takers Regime in New Zealand

A unique feature of the New Zealand banking system is the large portion of Non-Bank Financial Institutions, which, until very recently were not subject to either Reserve Bank New Zealand (RBNZ) or comparable disclosure requirements like registered banks (Hess and Feng, 2007). In a practical sense, these firms may offer any banking activities, but they are no officially permitted to call themselves a “bank”.

The Reserve Bank’s interest in NBDT was limited to the purpose of promoting the maintenance of a sound and efficient financial system, and avoiding significant damage to the financial system that could result from the failure of a NBDT (Wilson, 2009). NBDTs were not considered systemically important by the RBNZ; systemically important status was generally limited to the four largest banks – ANZ/National, ASB, BNZ and Westpac (Chetwin, 2006). A general warning about the vulnerability of NBDTs to a slowing economy was first highlighted in the RBNZ’s Financial Stability Report of October 2004 and then again in the later ones.

In 1983 the Securities Commission outlined the requirements of the investment statement and prospectus. Banks and NBDT’s were required to provide information to investors which would allow them to make more informed decisions on their investing. Typically, the investment statement does not require financial statements to be produced, and as a result, most retail investments are made without investors reviewing the financial statements. The required prospectus was more detailed. It included basic provisions on the trust deed, more detailed financial information and notes. However, the role of the Securities Commission was limited to ensuring compliance with the disclosure requirements of the current act and regulations. In April 2005, the Securities Commission stated in their report on disclosure by finance companies that “the commission does not have a role in relation to the prudential supervision of finance companies and does not comment on this” (Securities Commission Staff, 2004, p.1). After the failure of Bridgecorp Ltd, the Securities Commission stated that they were not responsible for the company nor were they able to intervene. In short, they can intervene only if a finance company does not provide the required information to investors (Securities Commission Staff, 2007a).

In December 2005, the New Zealand government agreed that the Reserve Bank should be the sole prudential regulator of the New Zealand financial system, including the NBDT sector. However, they did not set any specific requirements for financial institutions until 2009 (after a large number of financial institutions failed). The first wave of this regulation came into force in September 2008. The primary objectives were to maintain a sound and efficient financial system and to avoid significant damage that could result from the failure of a NBDT. The regulatory framework anticipated for NBDTs would give the Reserve Bank the role of licensing NBDTs, and developing and enforcing minimum prudential and governance requirements.

The prudential requirements for NBDTs are largely the same as the prudential framework for registered banks. However, a key difference is that the Reserve Bank relies on trustees to monitor

NBDTs compliance. It requires the finance company and its trustees to ensure that the NBDT's trust deed includes minimum capital ratios, quantitative liquidity requirements and related party exposure limits. If the trustee believes that there has been, or may have been, a material failure by the deposit taker to comply with these provisions, it is their responsibility to provide a report to Reserve Bank (Tyree et al., 2014).

Poor risk management practices were the main reason cited for the recent failure of several finance companies. While some finance companies failed to diversify their loan portfolios, others had inadequate security for their loans (Reserve Bank of New Zealand, 2010). The first requirement came into force on September 2009 in terms of risk management programme and required NBDTs to outline how they manage their key risks which must be approved by the applicable trustee. The programme must address the credit, liquidity, market and operational risks of the deposit taker and describe a process for regular review of the programme (Tyree et al., 2014). NBDTs also became subject to further requirements in terms of credit rating requirements in March 2010. Deposit takers are required to have a credit rating from an approved rating agency to assist investors in making informed decisions about their investments. This provides a simple way to compare the financial strength of different financial institutions. A poor credit rating indicates that there is a higher risk of defaulting on investor payments. The establishment of risk management regulations in September 2009, heralded the arrival of more regulation. In December 2010 other regulations were implemented around capital adequacy, related party exposures, liquidity and governance. Minimum capital requirements are now a basic prudential requirement for banks and NBDTs. Prior to this, many financial institutions had inadequate capitalisation ratios relative to the risks they were taking. This made them vulnerable to possible future failures in the event of adverse economic conditions. The trust deed specifies the minimum capital ratio that the deposit taker must maintain. For deposit takers with an approved credit rating, the minimum capital ratio must be not less than 8%, while for those without a credit rating, it must not be less than 10%.

Related party exposures have been an ongoing issue for NBDTs due to the tendency to abuse related party relationships. For example, related parties may be accorded preferential treatment or may not be subject to rigorous credit checks, as would be the case for non-related parties. Based on the Reserve Bank of New Zealand, related party transactions were a feature of many of the recent finance company collapses. The trust deed is required to establish a maximum limit, specified as a ratio against the institution's capital for related party lending. The limit must not be more than 15%.

A lack of liquidity was also a key factor in some of the recent collapses. New liquidity regulations require that trustees and NBDTs agree on appropriate quantitative liquidity requirements to be included in trust deeds. In addition, it is important that NBDT directors act in the company's best interests. This provides a level of assurance to security holders that their interests will not be prejudiced in favour of a related entity or individual. Since the 1 December 2010, NBDTs must have at least two independent directors and a chairman who is not an employee of either the NBDT or a related party. After May 2014, regulations also included the suitability of directors and changes of ownership. Trustee companies are responsible for supervising NBDTs' compliance with the Reserve Bank's prudential regulations. A list of the specific requirements which apply to NBDTs can be found in Appendix 1. Although the number of failures decreased after the implementation of these new regulations in 2010, there were several subsequent failures.

2.7 Summary

This chapter has provided a detail explanation of the diverse range of financial institutions, globally, drawing in particular on the United States, Europe and Australia. The chapter has discussed the need for international regulation in the finance sector and the evolution of the Basel framework. It has concluded by outlining the structure of the New Zealand finance sector and the regulations that govern it. The following chapter reviews pre-existing literature related to this study, focusing in particular on bank failure prediction models.

Chapter 3

Literature Review

3.1 Introduction

Having provided a broad overview of the global financial sector and the regulations governing it, this chapter offers a review of the literature on bank failure prediction models and in particular, focuses on CAMELS definitions. It discusses different aspects of corporate governance and their relationship with failure prediction, with reference to New Zealand. It also provides an overview of the literature on different prediction models and relevant theories such as the CAMELS theory, Agency theory, Stewardship theory and Agenda-setting theory. The chapter concludes with a discussion of the study's theoretical framework and a summary of the chapter's key findings.

3.2 CAMELS and Failure Prediction

In the banking sector, capital adequacy, asset quality, management competency, earning, liquidity and sensitivity to market risk measurements are covered by the CAMELS theory. This measurement strategy is based on The World Bank and International Monetary Fund handbook published in 2005. The CAMELS rating system was first adopted by the Federal Financial Institution Examination Council in 1979 and has since been recognised as an effective internal supervisory tool for examining a bank's condition (Barr, 2002).

Each of the six financial soundness indicators plays a different role in assessing a bank's stability. The first indicator, capital adequacy refers to the capital anticipated to retain a healthy balance between risk exposure (credit risk, market risk and operational risk) and daily operations (Dang, 2011). It is typically used to measure a financial institution's capacity to absorb unexpected losses (Narayanan, Thomas, and Abraham, 2018). The need to maintain sufficient capital ensures that an institution can continue to operate even if they experience losses (Pilbeam, 2005). Saif-Alyousfi, Saha, and Md-Rus (2017) have shown that Saudi banks with higher capital ratios have better performance and are ultimately more profitable.

As the risk of solvency in financial institutions often arises from impairment of assets, asset quality is the second factor. Grier (2007) notes that poor asset quality is the main reason for most banks failure. This indicator covers loan quality and the quality of asset portfolios. Saif-Alyousfi et al. (2017) found that Saudi banks with a higher non-performing loan are less profitable.

Management quality refers to the management's ability to evaluate corporate activities and ensure the business' efficiency (Dang, 2011). Grier (2007) considers management as the most important aspect of the CAMELS rating system because it plays a central role in a bank's success. It provides clear strategies and goals which guide business activities both domestically and internationally. Management is a decision mechanism to ensure the bank operates smoothly during any risk course (Christopoulos, Mylonakis, and Diktapanidis, 2011). Indicators of management efficiency are used to capture the significance of sound management in ensuring the health and stability of the financial institution and guarantees a bank 's growth and survival (Narayanan et al., 2018). As Ongore and Kusa (2013) explain, bank performance relies on management's capability to execute strategic plans and that, in their study of Kenyan banks, this significantly impacts bank profitability.

Earning quality reflects not only a bank or NBDTs' ability to generate profit, but also the elements which may influence earning sustainability (Dang, 2011; Narayanan et al., 2018). Earning quality can be measured using a range of data from different income sources, as well as profit and expenses because earnings demonstrate a business' ability to absorb losses without drawing on capital (International Monetary Bank, 2005). Earning quality has a strong relationship with an institution's financial performance(Fredrick, 2012). Grier (2007) believes that a stable profit can build public confidence. However, when the earnings or profits grow rapidly, it can be a sign of excessive risk-taking.

Since financial institutions have liquid liabilities (deposits) and relatively illiquid assets (loans), liquidity measurement shows a banking system's ability to tolerate cash flow shocks. Rudolf (2009) contends that the liquidity reveals the level of the bank's capability to fulfil its obligations. It measures an institution's availability of liquid assets in times of crisis (loss of market funding or an outflow of deposits). Chen (2014) states that liquidity is one of the factors that can improve a bank's competitiveness in the market.

This study considered Size as the "S" instead of "sensitivity to market risk." Much of the pre-existing literature has ignored sensitivity to market risk (see, for example, Distinguin, Rous, and Tarazi, 2006; Douglas et al., 2014; Oshinsky and Olin, 2006). Boyacioglu, Kara, and Baykan (2009) are one of the few to consider "sensitivity to market risk." It examines the ratio of trading securities to total assets, foreign assets to foreign liabilities, and net interest incomes to average assets. In a similar vein, Betz, Oprica, Peltonen, and Sarlin (2014) used a share of trading income as a proxy for "sensitivity to market risk." This study could not consider those variables in the CAMELS model due to either variable redundancy or unavailability. This study, like others (Avkiran and Cai, 2012; Kato and Hagendorff, 2010; Lanine and Vennet, 2006) uses size instead. The relation between company size and failure has been confirmed, probably because larger companies have access to bigger assets through leveraging and issuing shares when experience trouble (Cormier, Magnan and Morard, 1995; Lennox, 1999). Alkhatib and Harsheh (2012) found a positive relationship between bank size and bank performance. However, Saif-Alyousfi et al. (2017) declare that larger banks are less profitable and an increase in size decreases bank performance (Karim and Alam, 2013). In the case of New Zealand, there is evidence which suggests that ‘large’ companies are considered ‘small’ internationally (Van Peursem and Wells, 2001) due to their significantly small market size. This study compares each company’s total asset to the others to measure and incorporate their relative size (Van Peursem and Pratt, 2002).

Prior studies have shown that company failures can be predicted using financial ratio analysis (Ak et al., 2013; Altman, 1968; Beaver, 1966; Keasey and Watson, 1991; Ohlson, 1980; Wu, Gaunt, and Gray, 2010). These ratios can also be used to assess companies undergoing financial distress. For the first time, in 1968, Altman combined several ratios into a single predictive score known as the Z-score, which is a function of profitability, turnover, leverage and liquidity ratios (Douglas et al., 2014). Since the development of Z-scores, O-scores and Zeta, there has been considerable debate about the best set of predictor variables (Kumar and Ravi, 2007; Wu et al., 2010). Grice and Ingram (2001) contend that bankruptcy models do not retain their predictive accuracy when generalised across industries, countries or time periods. However, Van Peursem and Pratt (2012) classified 91.7% of failure among New Zealand listed companies by selecting Return on Asset (ROA), Sales to Assets, Leverages and Total Assets variables.

Kumar and Ravi (2007) reviewed several studies on banking failure prediction, using a variety of statistical tests. They addressed different financial ratios that typically fall within the CAMELS framework. Betz, Oprică, Peltonen, and Sarlin (2014) claim that the CAMELS rating system is also an internal supervisory tool for assessing the soundness of financial institutions on a uniform basis and is useful for recognising whether institutions need extra attention. Jordan, Rice, Sanchez, Walker, and Wort (2010) and López-Iturriaga, López-de-Foronda, and Pastor-Sanz (2010) used CAMELS’ proxies and different analysis methods to predict the United States bank failures during the global financial crisis. They found a high degree of predictability of the United States bank failure during this time.

In New Zealand, financial companies are unlisted (Wu et al., 2010), therefore we cannot use market data which increases the accuracy of bankruptcy prediction models. The criminal prosecutions that followed the finance companies’ bankruptcies suggest that financial disclosure would be unrepresentative of reality and there could be no difference in the financial ratios between failed and non-failed companies. Douglas et al. (2014) used disclosed information from failed New Zealand finance companies one year before failure and demonstrated that they had inferior CAMELS-based ratios than healthy companies.

3.3 Agency-related Information and Failure Prediction

There are two approaches to predicting failure; in the first method, one must study the accounting numbers, while in the second, one must also study additional company features (Argenti, 1976). Balcaen and Ooghe (2006) state that it may be inadvisable to rely just on financial information, as 'creative accounting' is more likely in times of financial distress. Non-financial information is less vulnerable to manipulation, which can be a significant signal of failure than variables based on financial information (Keasey and Watson, 1987). However, considering additional factors is in line with industry best practices (Douglas et al., 2014).

The concept of corporate governance can be concisely defined as the procedures and processes which conduct and control an institution (OECD Glossary of Statistical Terms). Governance is concerned with the systems, practices and procedures that govern institutions (Chenuos, Mohamed, and Bitok, 2014). Corporate governance has the potential to identify problem spots, where incentives are mismatched in a way that could lead to undesired firm behaviour or even system wide instability (Mehran and Mollineaux, 2012). It is associated with the corporation's internal performance and includes a set of regulated principles which link the institution's board of director, managers, its shareholders and stakeholders (OECD, 2004) to ensure the organisation achieves its goal (BBVA Microfinance Foundation, 2011). Vishwakarma (2015) explains that weak corporate governance and the absence of an integrated code of conduct can result in a critical situation, especially in the finance sector, because of the nature of their business. An integrated code of conduct plays an important role in the finance sector in restoring public confidence (Kansiime, 2009), creating trust among investors and attracting capital (Vishwakarma, 2015). It may reduce incidences of fraud and mismanagement. Odera (2012) studies the quality of corporate governance among Kenyan microfinance institutions and highlights their poor governance; there were no clearly defined roles and responsibilities in the system and a lack of management trust. Tadele and Rao (2014) declare that poor corporate governance forced Indian finance companies (Andhra Pradesh) to close down because of unethical loan practices. A lack of strong and efficient corporate governance policies is one of the main obstacles for the healthy growth of the finance sector. Good corporate governance rules are required to lessen information asymmetry and advanced performance in the finance sector (BBVA Microfinance Foundation, 2011). In New Zealand also, a lack of proper Agency-related information was also cited as one of the main factors for finance company failures (Douglas et al., 2014). Recently banking regulators and the Reserve Bank have stressed the need for effective governance practices in the banking system because failures and weaknesses in financial institutional governance contribute to the development of financial crises (Board of Governors of the Federal Reserve System, 2010, 2010a; Kirkpatrick, 2009).

Many studies have noted the close relationship between corporate governance and financial institution performance (Bassem, 2009; Mersland and Strøm, 2009). Hartarska (2005) examines this relationship using rated and unrated microfinance institutions in Central and Eastern Europe from 1998 through 2002. He uses management remuneration, board independence and diversity as corporate governance variables and finds that independent directors result in better performance. Kansiime (2009) finds that the Ugandan finance sector lost their investors due to lack of public trust. She contends that poor corporate governance results in failure among finance companies.

This study works on some aspects of Agency-related (or governance-related) information, such as board characteristics, related party transactions, audit quality, trusteeship, media coverage and firm maturity.

3.3.1 Board Composition

Many scholars recommend firstly investigating board of director characteristics, as weak corporate governance, in terms of management oversight and the board of directors, who drives excessive risk-taking and ultimately lead to the failure of financial institutions. As this demonstrates many failed companies have poor governance (Harris, 2007). The relationship between board size and firm performance is still an essential question for scholars. Some studies recommend having a large board to ensure better performance, while others argue that a small board has the same effect. Board of directors have two key responsibilities; these are advising and monitoring (Adams and Ferreira, 2007; Raheja, 2005). The advisory role involves expert advice, especially in critical circumstances. The advantage of a larger board size is that greater collective knowledge leads to better performance (Dalton, Daily, and Ellstrand, 1999; Dalton and Dalton, 2005). In addition to providing access to more resources and networking opportunities, larger boards also have the added benefit of expanding the number of individuals on whom the CEO and other executives can rely on for advice (Dalton and Dalton, 2005). The board of director’s second responsibility is monitoring. In short, they need to ensure that management teams work efficiently and pursue shareholders’ interest. They also need to remove ineffective management team members when needed (Guest, 2009). While a larger board size results in more efficient monitoring, due to assessing CEO performance from different perspectives, they may suffer from communication issues. It can be difficult to arrange board meetings and reach consensus. This may ultimately results in slow and inefficient decision making (Hartarska and Nadolnyak, 2007; Jensen, 1993). It may also mean that directors are less likely to share a common purpose, thus director free-riding increases. Keasey and Watson (1987) contend that there is a negative relationship between the number of directors and firm failure, arguing that a higher number of directors provides more alternative leadership (Kyereboah-Coleman and Osei, 2008) and lessens the probability of CEO authority (Bassem, 2009). In contrast, writing specifically about finance companies in Sri Lanka and India, Thrikawala (2016) suggests that larger boards, with more client representation, improves performance and reduces the possibility of failure. Adams and Mehran (2003) note that finance companies usually have a larger board than non-financial companies and their empirical findings demonstrate that larger boards improve firm performance.

In contrast, Pathan, Skully, and Wickramanayake (2007) argue that smaller boards of directors are more effective in monitoring managers and increasing firm profitability when measured using ROE and ROA. Hartarska and Nadolnyak (2007) recommend that an effective board size includes 10 to 12 members, whereas Mak and Kusnadi (2005) contend that five members are the maximum number needed for a valuable board. These different results prove that one board size is not ideal for all countries and all industries. Thrikawala (2016) contends that the optimal board size depends on the individual board's responsibilities, strategic direction and its funding needs. Chin, Vos, and Casey (2004) examine 426 annual observations of New Zealand firms across a five-year period and found that board size did not have any significant relationship with firm performance. Several others though (Hossain, Prevost, and Rao, 2001; Reddy, Locke, Scrimgeour, and Gunasekarage, 2008) have shown that the relationship between board size and firm performance is negative among New Zealand listed companies. Prevost, Rao, and Hossain (2002) find that board size has a significant negative relationship with Tobin's Q at the 1% level in New Zealand companies. Alternatively, Fauzi and Locke (2012) declare that board size has a significant impact on firm performance and note that in New Zealand the median board size is six members, which is smaller than the United States firms. Board size has a strong negative association with Tobin's Q which is significant at the 1% level. This demonstrates that a size affect is present in New Zealand as has been well documented in the United States and elsewhere. However, the smaller board size fits with New Zealand's smaller market characteristics.

This study, therefore, includes the number of BOD, any changes in directors, the number of appointed directors, and the number of resigned board members during the year as key elements of board composition.

3.3.2 Related-Party Transactions

Non-disclosure or incorrect disclosure of related party transactions in financial reporting can mislead investors about the true financial position and performance of a company. ISA (NZ) 550 related parties and other audit standards state that misstatement of related party transaction is a form of management fraud, and it is less likely to be detected as managers can easily dominate auditing procedures (Wu and Malthus, 2012). Therefore, related party transactions are one of the key aspects of corporate governance which may have a direct impact on firm performance and corporate failure.

Prior literature suggests that a significant amount of financial institutions lending occurs between related parties, which includes shareholders of the institution, their associates, family members and the corporations they control (La Porta, Lopes-De-Silanes, and Zamarripa, 2003). There are two different views about related parties lending. The optimistic assessment or information view (Gerschenkron, 1962) contends that related lending may improve credit efficiency in several ways. Lenders have close ties with their borrowers, and thus they are represented on the board of directors and can share their management information. This means that the lender may be better able to assess the borrower’s risk profile. In addition, both parties may reject policies that benefit one of them at the other’s expense. Therefore, related lending may be better because more information is shared and incentives are improved.

The pessimistic assessment or looting view (Akerlof and Romer, 1993) states that close ties between financial institutions and borrowers allow insiders to divert resources away from depositors or minor shareholders to themselves. If the banking system is protected by deposit insurance, a bank’s management can make loans to their own companies using nonmarket terms (in the cost of government). Even without deposit insurance, as long as the controller’s share of profits in their private company is more than their share of profits in the bank, they have enough incentives to divert funds.

Henry, Gordon, Reed, and Louwers (2006) study 48 American cases and found that company failure is directly related to related party loans. Louwers, Henry, Reed, and Gordon, (2008) come to the same result after examining 43 fraudulent cases in the United States. La Porta et al. (2003) examine 17 Mexican Banks in 1995 and find that money lent to related-parties had better conditions than that lent to unrelated parties. Related party transactions had a higher chance of default (a 33–35% probability). Having a diverse loan portfolio is also essential in order to lessen over-reliance on a specific industry or borrower (Altman and Saunders, 1998; Basel Committee, 1999). Kabir and Laswad (2014) state that the ability of a finance company to continue as going concern depends on the quality of assets (loans and advances). In 2009, the registrar of companies, Neville Harris, notes that a higher concentration of loans in the speculative property market results in poor asset quality. The Reserve Bank of New Zealand (2013), KPMG (2007) and Barker and Javier (2010) all find that failed New Zealand finance companies had higher-than-normal levels of related party lending and had a poor variety of assets. Wu and Malthus (2012) examine the related party transactions of 13 New Zealand finance companies and discovered four common characteristics; namely excessive lending without satisfactory securities, management fraud, deliberate non-disclosure of significant lending, and breaches of statutory requirements and agreements.

3.3.3 Auditing

Auditing plays a key role in protecting investors and maintaining market confidence. When company failure happens, the audit profession is brought into attention. It is not unexpected, as audited financial statements are important in ensuring the financial statements' credibility, including the issuing of going-concern opinions. Auditors evaluate the entity's ability to continue as going-concern, based on gathered information from audit procedures and obtained information about the management's plans. Although ISA (NZ) 550 related parties and other auditing standards note that it is less likely for auditors to detect fraud at a management level (rather than at an employee one) because managers can easily dominate control processes. However, receivers note that if financial failed companies had been thoroughly audited, it is less likely many of them would have continued in business for as long as they did. An audit failure occurs in two situations; when the auditors have not followed the Generally Accepted Accounting Principles (GAAP); and when the auditor does not publish a modified or qualified audit report where it is needed (audit report failure) (Francis, 2004). If auditors have issued a qualified, rather than unqualified opinions, there would have been a stronger imperative for trustees to step in earlier, before New Zealand experienced huge failures among finance companies (Vaughan, 2009). Mong and Roebuck (2005) state that a modified (but not qualified) audit report effectively works as a 'red flag' and (Carson et al., 2013; Holder-Webb and Cohen, 2007) summarise that firms which receive a going-concern opinion have a higher chance of failure. This opinion can act as an early warning of financial problems. The Registrar of Companies wrote that finance company audits ''lacked the rigour and analytical depth one would expect for entities managing substantial public investments'' (Harris, 2009, 11). Louwers et al. (2008) examine 43 United States companies where the auditors failed to recognise fraudulent related party transactions and established that these were the result of an absence of professional scepticism and lack of professional care. Carson et al. (2013) note that more than 60% of bankruptcies are followed by reported going-concern uncertainties.

Audit fees can be a proxy for the audit quality (Francis, 2004). When a firm has complex business operations, and the risk of financial misstatement is high, the demand for detailed monitoring audit is high. This requires spending more time and effort to understand the firm's financial reporting processes. Therefore, higher audit fees indicates higher audit quality; the higher fee either relates to more time allocated to the audit or provides an indication of an auditor's proficiency. High audit costs can be justified as a result of more time involved negotiating with the client. It is not easy to compare audit remunerations as the Big 4, on average, charge a 20% premium more than the other audit companies (DeFond, Francis, and Wong, 2000; Ferguson, Francis, and Stokes, 2003). Francis (2004) review empirical research, mainly from the United States over 25 years and found that audit failure rate is less than 1% annually, while audit fees are quite small, or less than 1% of aggregate client sales. He notes that the acceptable level of audit quality is achievable at a reasonably low cost. Carcello and Neal (2000) examine distressed firms during 1994 and did not find any evidence that audit remuneration has any relationship with company failure.

DeAngelo (1981) and Francis (2004) argue that audit quality is dependent on audit firm size, given that larger audit firms suffer a higher reputational loss from inaccurate reporting. The large Big 4 accounting firms have established brand name reputations, and they prefer to protect their reputations by providing high quality audits. After examining a sample of 6,568 United States firm-year observations for the period of 2003-2005, Francis and Yu (2009) declare that large auditors like the Big 4 are more likely to issue going-concern reports. Khurana and Raman (2004) note that litigation penalties are a motivation for the Big 4 auditors in the United States to provide high quality audits.

Furthermore, a longer lag between the end of the financial year and the auditor sign-off date could suggest greater negotiation between the auditor and company, or more work done to uncover financial irregularities (DeFond, Raghunandan, and Subramanyam, 2002; McKeown, Mutchler, and Hopwood, 1991). Geiger, Raghunandan, and Rama (2005) study 226 financially stressed companies that entered bankruptcy from 2000 to 2003, while Li (2009) examine 1681 companies in 2001 and 1780 companies in 2003. Both studies proved that there is a relationship between going-concern opinion and audit lag; higher audit lags increased the possibility of going-concern opinion and bankruptcy.

3.3.4 Trustees

The New Zealand Reserve Bank delegated the supervision of NBDTs to trustee companies. Trustees play an important oversight role; they have a fiduciary duty to ensure that payments are met, funds are received, and debt covenants are not breached. They need to ensure that prudential requirements are included in trust deeds and an issuer's operation complies with the trust deed (Wu and Malthus, 2013). A trust deed is an agreement between the trustee and deposit taker and consists of covenants to assure that the financial institution manages the business prudently. A trust deed may be issued to reflect the requirement in the regulation or affect individual circumstances such as the requirement to hold a higher capital ratio which is more conservative than the regulatory minimum. If the financial institution and trustees cannot agree on regulations or amendments, the trustee has the authority to include it in the trust deed without the permission of the other party (Javier, 2008). The Reserve Bank relies on trustees to report any actual or possible forms of non-compliance, including any breaches of the terms and conditions of the trust deeds. As an assessment of the New Zealand financial sector in 2003 shows, regulatory functions have relied on private supervisors, such as corporate trustees (The International Monetary Fund, 2014). The report noted that supervisors were not performing their role adequately. In addition, the Commerce Committee (2011) argues that some trustees did not have experienced staff that understood the loan risk profiles. When a trustee has a supervisory role, they need to be an expert in the field so that they understand the nature of the business and understand the risks. The 2006 NBDT failures may demonstrate that the directors of these financial institutions had not received enough comment from their trustees and as a result, they managed the business according to their own interest (Wilson, 2009). Wilson, Rose and Pinfold (2013) reveal that even if the trustee were aware of any breach, they agreed to amend the definitions in the trust deed (like changing the definition of related party transaction). The probability of trust deed amendment is higher close to failure. These collapses highlight trustees' weak performances in areas including, poor trust deeds, a lack of transparency in relation to their roles and a lack of independence and accountability (Wu and Malthus, 2013).

3.3.5 Media

Media, and the press, in particular play a critical role in shaping public opinion (Cohen, Ding, Lesage, and Stolowy, 2017) about companies. Thus, it operates as a monitor on behalf of the general public. Dyck, Morse, and Zingales (2010) find that fail prediction relies not only on corporate governance actors like auditors and trustees but also on several non-traditional players (like media). Different access to information, as well as reputational inducements, can justify this pattern. Miller (2006) explains that the business press, in particular, was instrumental in bringing many of the financial frauds into the public arena. For example, Fortune magazine published the first negative report on Enron and wrote reports on Healthsouth and Worldcom. McCarthy and Dolfsma (2014) and Gentzkow and Shapiro (2006) suggest that by choosing what events to report upon, how much and how frequently to report on an event, and by choosing the framing and tune of story, media influence public opinion. Van Peursem and Hauriasi (1999) analyse the professional reputation of auditors within New Zealand by examining the content of articles in the press which reference auditors. They discovered that press coverage in New Zealand, of the auditing profession appears to be widely influenced by news production necessities and by the desire to entertain. As a result, the auditor is portrayed as either elite expert, or incompetent/unethical player in major news events.

Media can affect not only a company's reputation (Vogel, 2006) but also individual executives and directors (Dyck et al., 2010; Zingales, 2000). This causes them to be vulnerable to negative shocks related to their reputations. For example, bankrupt-ridden directors may lose their current job and find it hard to find future employment. As Dann (2008) and Parker (2010) explain, media suggested that some financial company accounts were unreliable and contained errors of judgement. In response to the threat of journalistic evaluations of corporate misbehaviour, directors are more likely to advise their companies to act in socially responsible ways (El Ghoul, Guedhami, Nash, and Patel, 2016). Several studies have shown that extra-legal institutions like media play a critical role in shaping corporate decisions (Atanassov and Kim, 2009; Dyck and Zingales, 2004; Haw, Hu, Hwang, and Wu, 2004). The Press' influence on public opinion is greater when it reports bad news rather than when it reports good news; media shaming is a particularly effective tool (Borden, 2007). Dyck et al. (2010) describe media as a "smoking gun" indicator when they are directly discovering the failure. Although we cannot expect the media to act as an effective monitor in the case of small companies, he noted that media is responsible for more than 13% of failure detection rates. Therefore, studying press coverage of company failure sheds lights on the public view.

3.3.6 Firm Maturity

A corporation's maturity is defined by the number of years the company has been in the market (Hartarska, 2005; Marimuthu and Kolandaisamy, 2009; Mersland and Strøm, 2010; Microfinance Information Exchange, 2007). It is normally encompasses the years between a firm's start date and the submission year of data (Microfinance Information Exchange, 2007). Agrawal and Gort (1996, 2002) suggest that mature companies have more knowledge and skills which they have obtained via general day-to-day activities linked to hiring and training their staff. Caudill, Gropper, and Hartarska (2009) note that greater maturity provides managers and employees with more learning and experience opportunities in particular market environments. Firm maturity is also a key factor that creates a reputation and builds faiths among investors and borrowers. It indicates that a company is successful and will be in the market for a long time; this enhances long term social values which is reflected in greater firm performance (Navajas, Schreiner, Meyer, Gonzalez-Vega, and Rodriguez-Meza, 2000).

However, a long business life may have a negative impact on a firm's performance. Maturity can bring rigidity, inactivity and a reluctance to change (Loderer and Waelchli, 2010; Tripasa and Gavetti, 2000) which may diminish a firm's performance over time and ultimately lead to failure. For instance, Loderer and Waelchli (2010) explain that in high-tech companies, failure to adopt new technologies will lead to inefficiency and lower performance compare with younger firms in the same industry. Nurmakhanova, Kretzschmarand Fedhila (2015) note that older finance companies prefer to serve fewer richer clients with larger loans, which ends up with losing their potential borrower. This strategy can also lessen asset quality; reduce performance and increase the odds of failing. Hartarska and Nadolnyak, 2007 and Mersland and Strøm (2009, 2010) all found a positive relationship between the age of a finance company and the number of active borrowers. Nurmakhanova et al. (2015) note that a finance company's maturity is positively correlated with financial sustainability. Older companies are more efficient in monitoring costs and increasing profitability and ROA (Caudill et al., 2009; Kyereboah-Coleman and Osei, 2008).

3.4 Prediction Models

Predicting bankruptcy in business, especially in the financial sector is an essential skill. It is widely studied topic in the business intelligence field (Chen, 2011; Serrano-Cinca and Gutiérrez-Nieto, 2013; Sun, Li, Huang, and He, 2014; Yu, Miche, Séverin, and Lendasse, 2014; Zhou, 2013). In recent years, prediction models have become more sophisticated to account for the effects of financial crises or other outstanding business episodes (Mokhatab Rafiei, Manzari, and Bostanian, 2011; Nassirtoussi, Aghabozorgi, Wah, and Ngo, 2014).

The critical aim of failure prediction is to separate those institutions that will not be able to accomplish their financial obligations in the future from those that can. Obviously, there is no model which can predict with 100% accuracy how a company will behave in the future. However, scholars are increasingly looking for different algorithms to develop more accurate prediction models. The methods of prediction modelling have changed greatly since Beaver (1966) and Altman's (1968) pioneering works.

Beaver's dichotomous classification test was a simplified univariate discriminant analysis that applied an end-point to a financial ratio. Soon after that, Altman (1968) appoints a Multiple Discriminant Analysis (MDA) model, now known as the Z-score model. He uses MDA on a classified dataset of 33 pairs (failed and non-failed manufacturing companies) to build a financial ratio based model for predicting corporate failure (Duda and Schmidt, 2010). The success of Altman's Z-score model marked the beginning of fail prediction models. The Z-score model is mostly used in the studies as a base model in comparison with newer models (Altman, Marco, and Varetto, 1994).

Altman's model has been severely criticised and its weaknesses have become more noticeable. The first weakness relates to the multivariate normal distribution assumption of the variables; a sample is randomly selected from the populations of failed and non-failed companies. The unequal distribution matrices in linear equations make it hard to understand and interpret the role of explanatory variables (Eisenbeis, 1977). MDA does not help with predicting failure; it is only a dichotomous classification for failed and healthy companies (Dimitras, Zanakis, and Zopounidis, 1996). Following the revelation of MDA's faults, its popularity declined, with a concomitant rise in conditional likelihood models (conditional on a vector of predictive variables) to describe bankruptcy (Li, 2014).

Meyer and Pifer (1970) established the Linear Probability Models (LPM) using Ordinary Least Squares (OLS) regression for failure prediction. However, the problem with this method is that it violates failure probabilities (they can go outside the range of 0 to 1). Martin (1977) introduced Logistic Regression (LR) or Logit analysis to predict bank failure. Ohlson developed his LR model (named the O-Score model) for failure prediction in 1980. As LR has fewer variable requirements than MDA and its predicted probabilities are circumscribed between 0 and 1, it soon became the most popular failure prediction model. While LR has been used by several scholars (Dugan, Ingram, and Tennyson, 1990; Gilbert, Menon, and Schwartz, 1990) it has still be criticised (Kim, 2011; Li, 2014; Lin and McClean, 2001). Zmijewski established probit regression in 1984, which is sometimes used in prediction studies, but considerably less than LR (Grunert, Norden, and Weber, 2005; Lennox, 1999).

Although these three main statistical algorithms (MDA, LR and probit) have been implemented broadly in prior studies, they have also been censured. There has been some criticism of these models due to their determination of a dichotomous dependent variable, the volatility of the data, the sensitivity needed for collecting samples, variables and optimisation indicators (Balcaen and Ooghe, 2006). While these are common problems in all the prediction models (Li, 2014), the main issue in the models above, is the time dimension; data from different years pool together

(Altman, 1968; Zmijewski, 1984). This can lead to a bias in sample selection (Shumway, 2001) which makes it hard to interpret both the variables and the results (Edmister, 1972; Joy and Tollefson, 1978).

Survival analysis was a statistical method originally designed to determine an organism's time of death. When the time dimension is added to the parameters, covariates and regression models, prediction becomes dynamic. Cox (1972) established the Cox proportional hazard model, which was adapted by Cox and Oakes in 1984 (it became the continuous time hazard model). Lane, Looney, and Wansley (1986) were the first to use it for bank failure prediction. Shumway's (2001) discrete time hazard model features some improvements on these earlier models, particularly in regards to the calculations and the nature of covariates as the financial related ratios and macroeconomic variables in the companies are checked periodically. Using a dataset of 300 bankruptcies (1962-1992), he demonstrates that the static model is inappropriate for forecasting bankruptcy because of the nature of bankruptcy data. Static models are not capable of capturing the dynamic nature of a company's financial structure, as the characteristics of firms change from year to year (Duda and Schmidt, 2010). Shumway explains that most forecasters choose to observe each bankrupt firm's data in the year before bankruptcy. Choosing when to observe a firm's characteristics (that is, a year before bankruptcy), creates an unnecessary selection bias effects. Shumway (2001) suggests that the time-varying hazard model is superior to the traditional static forecast model in that it incorporates time-varying explanatory variables and treats a firm's health as a function of its latest financial condition. It produces more efficient out-of-sample forecasts.

Nam, Kim, Park, and Lee (2008) compare static logit with hazard models using panel data from a sample of 367 Korean companies, between 1999 and 2000. They show that dynamic models with time-varying covariates have superior performance over static models, especially when the market-driven variables are added to the estimation. Their results are in line with Bellotti and Crook (2009) who show when macro-economic indicators are included, the accuracy of the prediction model improves considerably. Although earlier studies such as Nam et al. (2008) and Männasoo and Mayes (2009) compared the accuracy of both models in predicting bankruptcy, more recent empirical studies (Betz, Oprică, et al., 2014; DeYoung and Torna, 2013; Hong and Wu, 2013) apply the time-varying hazard models in bank failure prediction by using one-year lagged explanatory variables (Brown and Dinc, 2005; Brown and Dinç, 2011; Männasoo and Mayes, 2009; Molina, 2002; Wheelock and Wilson, 2000).

With the development of machine learning in the 1970s, Artificial Neural Networks (ANN or NN) became more common for predicting bankruptcy. The process of this system is modelling the communication and information processing mechanism in the human brain. There are several types of artificially intelligent expert system models in terms of topology employed: Back Propagation NN (BPNN), Genetic Algorithm (GA), Support Vector Machines (SVM), Bayesian Networks (BN), etc. Artificial Intelligence systems have many derivatives due to their various modifications. Tam (1991) used BPNN to predict bank failure in Texas. His results show that this model is more precise than the DA model. Atiya (2001) and Tsai and Wu (2008) used NN to predict failure. Beck, Katz, and Tucker (1998) used GA to predict failure among 37 Finnish companies. They contend that GA provides better results than DA and logistic regression. Shin, Lee, and Kim (2005) also found that SVM is better than BPNN in predicting corporate failure. Paliwal and Kumar (2009) expanded two different NN models and compared their prediction accuracy with logit regression and MDA models. They found that general regression performed significantly better in comparison with their NN models (back propagation and probabilistic neural network).

Kumar and Ravi (2007) and Aziz and Dar (2004) both provide a detailed discussion on intelligent techniques. They contend that these methods are not as straightforward as statistical methods and that expert opinion is needed to establish the initial rules and interpret and/or compare results. Shin and Lee (2002) note that it is hard to find a proper NN model which can reflect the problem features; there are numbers of learning methods, parameters and network designs. Additionally, they point out that NNs design is like a black box; you cannot easily understand the ultimate rule that the model achieves. Yang, Platt, and Platt (1999) also highlight problems like scholars have to explain the results of the back-propagation model or describe how the results were obtained.

3.5 Theories Related to this Study

CAMELS theory explains how the soundness of financial institution can be assessed through financial ratio; whereas, agency theory describes how to best organise the relationship between the principal and the agent to minimise agency conflicts. Agency problems are the result of conflicting interests between managers and owners under conditions of asymmetric information. Stewardship theory focuses on the conditions on which managers' strategies are based on, as well as institutional best interests. Stewardship theory aims to reduce the conflict by maximising financial performance.

This study uses Agenda-setting theory which explains the impact of media on corporate governance and can be used to predict failure. In terms of theoretical background, Agenda-setting theory is similar to Stewardship theory. This section covers the theories which are used to support this study and research questions.

3.5.1 CAMEL(S) Theory

The unbalanced economic situation of the last few decades raises questions about how to measure the soundness of the banking system. While creditors, especially large size depositors, are inevitably interested in potential losses, regulatory agencies need to be conscious about situations requiring their intervention. Beaver (1966) established the theory of financial ratio analysis; he viewed businesses as liquid assets' holders. Beaver showed that failure could be predicted using through financial ratios for at least five years before failure. However, Beaver focuses on companies rather than the finance sector.

Martin highlighted the need for risk management strategies in the finance sector in 1977. He worked on 5700 Federal Reserve member banks in the United States between 1970 and 1976. He developed statistical techniques to analyse financial statements and revealed the factors one can use to measure bank financial condition, such as the relevance of capital (C), liquidity (L), earnings (E) and asset quality (A). Together with two other variables (that is, management (M) and market sensitivity (S)), these factors became the foundation of the Uniform Financial Rating System (UFRS) established in November 1979 (King, Nuxoll, and Yeager, 2005). This rating system was accepted by the National Credit Union Administration in October 1987 (Dang, 2011). It has demonstrated its usefulness as an internal supervisory tool for assessing the soundness of a financial institution and identifying the firms with problems (U.S. Uniform Financial Institutions Rating System 1997, p.1)

The CAMELS theory attempts to put these elements together and create a structural framework for bank supervisors (Gilbert, Meyer, and Vaughan, 2002). As these authors note, banks that have inferior CAMELS ratings over a three year period have a much greater risk of failure. King et al. (2005) provide empirical indications that the features and qualities of failing banks have changed over the last ten years and suggest that CAMELS ratings provide an early-warning system. Researchers have used the CAMELS framework to check the financial health of commercial banks in Kenya (Ongore and Kusa, 2013), Nepal (Baral, 2005), Vietnam (Dang, 2011) and India (Sangmi and Tabassum, 2010). Kumar and Ravi (2007) provide an overview of 14 studies that use the CAMELS framework to predict failure in the banking sector. However, prior literature about financial failure may not apply to the private New Zealand finance sector.

3.5.2 Agency Theory

Ross (1973) investigated the costs involved with a lack of goal congruence between two parties, whether between a principal and agent (PA) or between principal and principal (PP). Jensen and Meckling (1976) developed the concept agency theory. They defined an agency relationship as "a contract under which the principal (s) engage the agent to perform a service on their behalf, which involves delegating some decision making authority to the agent [P. 308]." Agency theory is based on two concepts; asymmetric information and party incentives. According to Jensen and Meckling (1976), if both parties have a maximum utility, it is likely that the agent will not always act in the best interest of the principal. In contrast, they note that while principals seek to maximise their wealth, managers may have other interests to maximise their utility through the overconsumption of perquisites and empire building. A conflict of interests between managers and owners leads to an asymmetric information flow (Chrisman, Chua, and Litz, 2004). In addition, the separation of ownership and control can also lead to situations where management manages earnings in order to meet market expectations. It is challenging for the principal to monitor the agent's behaviour due to degrees of asymmetric information flow between the principal and the agent. This can lead to a moral hazard. Despite these principal-agent relationships, each party is aware of prospective distortions and the need to realign incentives and design corporate governance structures (Fama and Jensen, 1983).

Fama and Jensen (1983) contend that agency problems can be addressed firstly by addressing the character of the board of directors. Boards of directors play an important role in controlling agency problems, especially by monitoring executive management. They enhance the principal's value and reduce management opportunism by providing an impartial and independent monitoring service. Additionally, asymmetric information and the limited capacity to process information and deal with complexity (Simon, 1957) often result in using external supervisors, like auditors and trustees, to align principal and agent's interests.

The second type of conflict, between the principal and principal, appears when the majority of shareholders of the company use the firm's resources in a way that disadvantages minority shareholders (Anderson and Reeb, 2004). PP problems tend to occur when the major shareholder is a related party, like an individual or a family member. A related party will have incentives for both expropriation and monitoring, with a higher tendency for expropriation (Wellalage, 2012). RP transactions can be a component of overall formal or informal compensation packages, where RP transactions are substituted for cash-based compensation to directors, or provide more liquid forms of compensation to directors, especially when they have ownership in the company. In agency theory, RP transactions also raise concerns that managers will over consume perquisites, which favours managers over principals (Hölmstrom, 1992; Hölmstrom, 1979; Jensen and Meckling, 1976).

Despite the issues identified above, depositors still invest their money in such companies. In New Zealand, there has been rapid growth in the finance sector which has been accompanied by an increase in deposits, from $5.1 billion to $7.1 billion from 2004 to 2007. Thus, there is a need for increasing levels of regulated corporate governance. Although the New Zealand banking system has been regulated by The Reserve Bank for many years, a large number of NBDTs were exempt from Reserve Bank regulations and comparable disclosure requirements that registered banks must adhere to. The lack of corporate governance in this system resulted in the bankruptcy of several finance companies between 2006 and 2010. Some of these issues have been addressed by new regulation introduced in September 2009.

3.5.3 Stewardship Theory

A counter strategy to agency costs theory is stewardship theory. Davis, Schoorman, and Donaldson (1997a) developed this theory. It defines the relationship between principal and agent and is based on an intensive leadership philosophy adopted by an institution's owners. Stewardship theory focuses on circumstances in which a steward concentrates on improving organisational performance so to satisfy the majority of the stakeholders; personal interests are aligned with the objectives of the principals (Guo, 2011; Wellalage, 2012). In the steward role, manager strategies are institutionally centred and reflect the best interests of the principals. Steward managers attempt to reduce agency conflicts by maximising the company's financial performance.

The steward must find a balance between personal interest and an institution's objectives. S/he must meet his personal needs through working towards business success. As Davis, Schoorman and Donaldson (1997b) note:

> *"The steward's opportunity set is constrained by the perception that the utility gained from pro-organisational behaviour is higher than the utility that can be gained through individualistic, self-serving behaviour. Stewards believe their interests are aligned with that of the corporation and its owners. Thus, the steward's interests and utility motivations are directed to organisational rather than personal objectives." (p. 56)*

As explained earlier, prior to late 2009 non-bank deposit takers in New Zealand were not subject to any specific regulation (The Reserve Bank had not set any specific requirements). In short, an institution's performance was dependent on the inside managers and external supervisors.

3.5.4 Agenda-Setting Theory

The question of whether or not media influence human behaviour remains an interesting question which researchers have spent almost a century to identify. Walter Lippmann addressed this issue in 1922 in a chapter titled "The World Outside and the Pictures in Our Mind" (McCombs, 2011). Several decades later, Benard Cohen (1963) expanded this notion when he said, "The press is significantly more than a purveyor of information and opinion. It may not be successful much of the time in telling people what to think, but it is stunningly successful in telling readers what to think about"(p. 13). His findings became the basis for what we now call the agenda-setting function of mass media. In 1986 McCombs and Gilbert used a content analysis of a local election to illustrate how public opinion is shaped by media representations of the world. They argued that public opinion is shaped by the prominence journalists place on certain news items (Gilbert and McCombs, 1986; McCombs and Valenzuela, 2007).

It is clear that apart from information from family and friends, media has a hugely influential role. Most of what we know about the world comes to us through the media. While it is not necessary to notify public about obvious news like inflation, as routine purchases uncover its presence, they need to alert about economic issues like any economic or industry crisis which the main source of information is the news media.

The amount of business news in the mass media has increased significantly over the last two decades. The growth of business news reporting is critical to companies struggling to manage their issues because customers and external stakeholders rely on the news to learn more about the companies they invest in (Chen and Meindl, 1991; Deephouse, 2000). Media reports on financial disclosures and corporate governance rose dramatically after Enron times (Carroll and McCombs, 2003). For instance, several scholars have studied the impact of media on corporate governance (Dyck, Volchkova, and Zingales, 2008; Dyck and Zingales, 2002; Dyck and Zingales, 2004). Likewise, others have examined the role of the media in predicting corporate fraud in the United States (Dyck, Morse, and Zingales, 2007; Miller, 2006).

There are many recorded claims of journalists failing the public by not providing enough essential public affairs news – a common complaint in New Zealand (Cook, 2002; Dahlberg, 2005; McGregor, 2002). These criticisms indicate that the public expects and believes that journalists play a key role in informing and educating the public (Singer, 2003).

3.6 Theoretical Framework

This study's primary aim is to examine the effect of the CAMELS-based ratio and Agency-related information in predicting failure among NBDTs in New Zealand. Figure 3-1 provides the conceptual framework of this study.

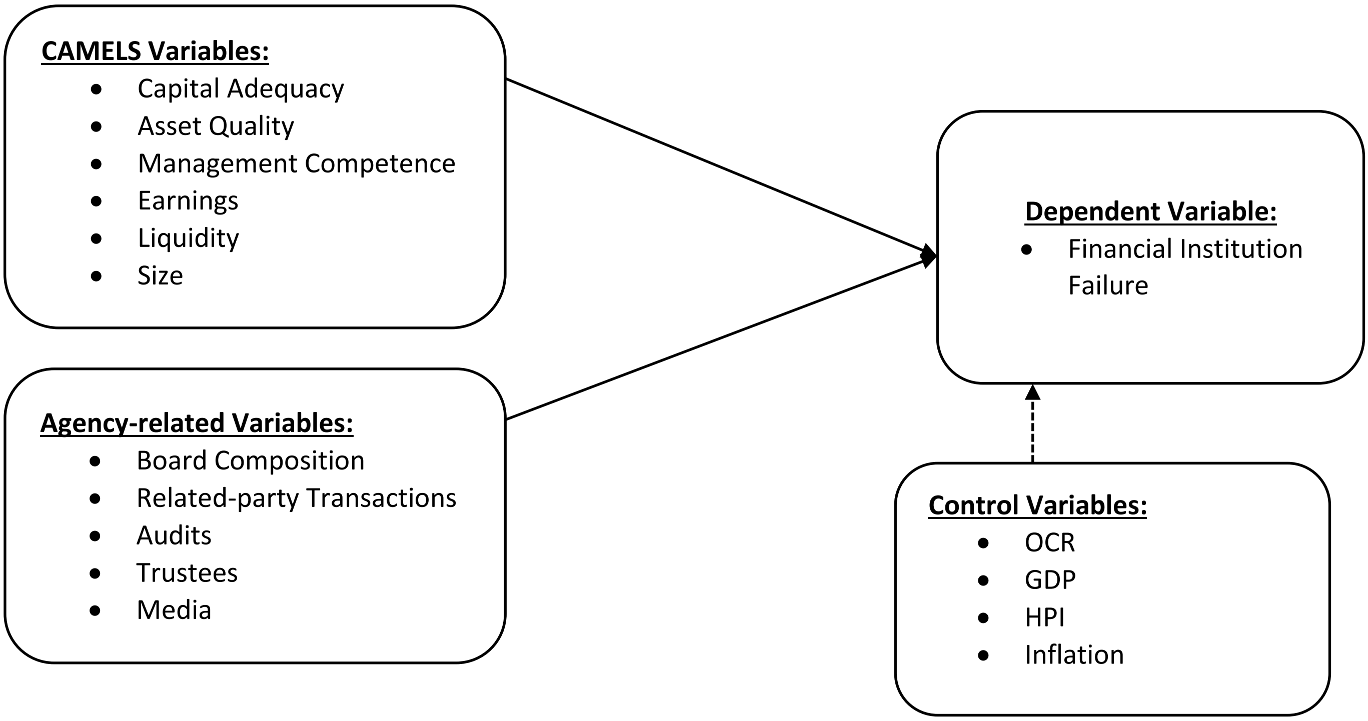

Figure 3-1 Theoretical Framework

3.7 Summary

This chapter has revealed gaps in knowledge about CAMELS, including aspects of corporate governance, which include the board of director composition, related party transaction, auditing, media coverage, maturity and failure prediction in New Zealand. The evolution of prediction models was developed afterwards. The CAMELS theory has been explained in support of the impact of the financial ratio in fail prediction. Agency theory, Stewardship theory and Agenda-setting theory have been briefly outlined as all support the effect of corporate governance on predicting failure, especially among New Zealand financial institutions. The theoretical framework is provided in the last section. The next chapter presents the research design and measurements used in this study.

Chapter 4

Research Design

4.1 Introduction

Having provided a broad review of literature and related theories, this chapter describes the methodological features of this study. It contains information about the data collection methods and the determination of the sample size. It also outlines the method used to quantify the variables used in developing research questions. After presenting the variables used in this study, it provides an overview of the logit model and the hazard models. It also addresses issues of model validation and performance accuracy. The final section outlines the key points of the chapter.

4.2 Sample and Data Collection

A high rate of failure among finance companies occurred between 2006 and 2009. However, the definition of failure plays an important role in scrutinising failure predictions. In this study, failure is defined as a moratorium, receivership or liquidation. Moratorium describes a process where creditors are unable to enforce debts (Douglas et al., 2014). Receivership refers to the process where a receiver manages a business on behalf of the security holders (Receivership Act 1993). Liquidation describes the process where a formal appointee takes over and controls a firm’s assets in order to pay creditors (Companies Act 1993). This study follows Douglas et al.'s (2014) work and does not consider a company failed when it is reorganising or restructuring as this can be due to other reasons. This study concentrates on failed companies between 2006 and 2010, before new requirements came into force in September 2009. It must be noted that ten companies went into receivership between April and November 2010. As the financial data during the year of failure is often unavailable, the study compares the published financial data of failed companies over 2005/06-2009/10, for the three years prior to the year the company failed. Therefore, companies which failed in 2010, whether they used a March or June balance date, their last financial accounts (2009) compiled before implementing of new requirements in September 2009. The total number of failed companies between 2006 and 2010 was 61 companies, based on the “Deep Freeze List” published by interest.co.nz. However, only firms with three years of consecutive data were included in this study. The sample thus consists of 35 failed financial companies that are uniquely matched in terms of asset size, with 35 finance companies that did not fail during the same period. The control sample is matched based on asset size. It means that the selected healthy companies are the result of matching one-to-one with the failed companies. After selecting the matched healthy company, data was collected for the same year as the failed company. This study thus eliminates time differences and increases validity.

After the new requirements came into force in September 2009, six more finance companies failed (2011 and 2012). However, data was only available for three of them. This study also used these three failed companies (they were also matched with three healthy companies) as an ex-post sample to check the accuracy of the prediction model. Table 4-1 illustrates the sample selection process over the period from 2006 to 2012.

The sample finance companies are not listed and not covered by traditional database source (or the disclosure requirements of the New Zealand Stock Exchange). Therefore, financial data was collected from annual reports published in the New Zealand Companies Office database. Non-financial variables were manually collected from the New Zealand Companies Office. Media information was collected from two main New Zealand newspapers; the NZ Herald and Stuff news.

Table 4-1 Number of Finance Companies Included in the Dataset Based on Failed Year

Year	Total Number of Failed Companies	Study Sample
2006	4	2
2007	15	10
2008	29	13
2009	3	2
2010	10	8
2011	4	3
2012	2	0

4.3 Variable Measurement

The following provides an explanation of the variable measurements as shown in Tables 4-2 and 4-3. The tables summarise the measurements and source of data for all of the variables in this study. Table 4-2 outlines CAMELS variables, while Table 4-3 indicates Agency-related variables.

Table 4-2 CAMELS Variables

CAMELS Variables	Measurement	Source of Data
Capital Adequacy: *TE-TA* *TA-TL* *GLOAN-TA* *TL-TE*	 Total equity/total assets Total assets/total liabilities Gross loans and advances/total assets Total liabilities/total equity	Annual report
Asset Quality: *IMPAIR-TA* *DOUBT-GLOAN*	 Impaired assets expense/total assets Provision for doubtful debts less bad debts recovered/gross loans and advances	Annual report
Management Competence: *OE-OR* *OE-TA*	 Operating expenses/operating revenue Operating expenses/total assets	Annual report
Earnings: *NPAT-TA* *NETINT-TA* *NPAT-TE*	 Net profit after tax before abnormals/total assets Net interest income/total assets Net profit after tax before abnormals/total equity	Annual report
Liquidity : *CA-TA* *OCF-TA*	 Current assets/total assets Net operating activity/total assets	Annual report
Size: *TA*	 Total asset	Annual report

Table 4-3 Agency-related Variables

Agency-related Variables	Measurement	Source of Data
Board Composition: *NUMDIR* *DIRCHANGE* *DIRAPPOINT* *DIRRESIG*	 Number of the board of directors member at year-end No change in director/s during the year = 1, otherwise 0 Number of directors appointed through the year Number of directors resignations through the year	Annual report/ Prospectus/ Companies office
Related party and lending concentration: *RELAT_TA* *RELAT_GLOAN*	 Related party lending/total assets Related party lending/loans and advances	Annual report
Audit: *BIGN* *MODIFIED* *AUDITLAG* *AUDREM*	 If Auditor is Big 4 = 1; otherwise 0 Any modification to the audit report = 1; otherwise 0 Number of days from the end of financial year to the audit's sign off date Audit remuneration	Annual report
Trustee: *TRUSTEE_X = Covenant* *TRUSTEE_Y = Perpetual*	If Trustee X is trustee = 1; otherwise 0 If Trustee Y is trustee = 1; otherwise 0 If Trustee Z is trustee = 1; otherwise 0	Companies office

TRUSTEE_Z = Guardian AMENDED	If the trust deed was amended over the year before bankruptcy = 1; otherwise 0	
Firm Maturity: *AGE*	The time in years from incorporation year up to the year of data collection	Companies office
Media: MEDIA	How many times the media is referred to the institution	NZ Herald/Stuff

4.3.1 Dependent Variable

In this study, the dependent variable is whether a finance company has failed or not. In the case that a company eventually fails then it is assigned dummy variable "1," which is allocated to the company for the entire three-year observation period before failure. A company that has not failed (up to the date of data collection (2017)) is considered healthy. In this case, a dummy variable of "0" is assigned for the entire three year period.

4.3.2 Independent Variables

Financial failure indicators are assumed to be a function of CAMELS and Agency-related variables. There are 14 Agency-related variables of board composition, related party transactions and lending concentration, audits, trustees, firm maturity and media variables. A total of 27 variables are used in this study. The measurements and their related variables are explained below.

CAMELS Variables

It is common for regulators and supervisory agencies to use variables in each of the CAMELS classifications for monitoring bank risks, developing early warning systems, and ensuring the safety and soundness of a banking system (Boyacioglu et al., 2009; Cihak and Poghosyan, 2009; Cole and Gunther, 1995; Curry, Elmer, and Fissel, 2003; DeYoung, 1998; Kumar and Ravi, 2007; Oshinsky and Olin, 2006; Ravisankar and Ravi, 2010). However, as the variables used to determine CAMELS ratings are not publicly available (Jin, Kanagaretnam, and Lobo, 2011), after considering the literature and accessibility of data, the following variables were included under each CAMELS category:

Capital Adequacy (C)

Cihak and Poghosyan (2009) provide two main reasons for not using the regulatory Tier 1 capital to risk-weighted assets. Firstly, this information is not available publicly, and secondly, it is subjective and therefore it is easy to manipulate the calculation of risk-weighted assets. Most scholars, like Pille and Paradi (2002), use the total equity to total asset ratio to measure capital adequacy. It is seen as a useful ratio for predicting if the company is at risk of the failure, Schaeck (2008) also note equity mitigates asset value and payments to debt holders.

In finance companies, a significant portion of assets is tied up in loans with the highest potential of unanticipated lost. Deposits contribute a major proportion of liabilities. Financial institutions with various proportions of assets to liabilities could have a funding imbalance. Hua (2006) notes that the China Banking Regulatory Commission (CBRC) performs off-site checking of financial companies' asset-liability ratios on a regular basis. Douglas et al. (2014) used asset-liability ratio as a proxy for capital adequacy in predicting failure among New Zealand finance companies. The gross loans and advances to total assets ratio reveals the possibility of default risk if the loans remain unpaid. Both Swicegood and Clark (2001) and Tam and Kiang (1992) used this ratio and suggest it is a good predictor of failure among financial companies.

The next ratio used to measure capital adequacy is total liability to total equity. In July 2009, the Reserve Bank of New York declared that the leverage ratio predicted bank failure as well as more complex risk-weighted ratios over one or two-year horizons.

Canbas et al. (2005) argue that the greater the capital adequacy ratio, the greater the financial strength of a bank. In short, they have a lower default risk. Capital adequacy ratio displays a bank's internal strength to tolerate losses during the crisis (Ongore and Kusa, 2013). This study thus uses the four ratios discussed above; total equity to total asset, total assets to total liabilities, gross loans and advances to total assets and total liability to total equity as proxies to account for capital adequacy.

Asset Quality (A)

Finance companies' most risky assets are loans. Asset risk can be evaluated entirely using balance sheet term like loans to total assets – since loans are riskier than securities and cash assets (Martin, 1977). Previous studies have found a notable difference in the asset quality of healthy and distressed financial companies (King et al., 2005; Sinkey, 1975). Frost (2004) notes that asset quality determinacies focus on the proportion of non-performing loans which are the proxy for asset quality. Loan quality is an important variable that has been commonly evaluated by impairment assets (non-performing loans) to total loans or total assets, and the provision of bad loan to total assets or total loans. Curry et al. (2003) propose that the quality of credit loans is correlated with the probability of changes in CAMELS ratings, reflecting problem and non-problem institutions. Both King et al. (2005), Swicegood and Clark (2001) contend that the provision of doubtful debt to gross loans results in poor asset quality and indicates a higher chance of failure. This ratio recognises that financial companies may have used aggressive lending strategies (Jaikengkit, 2004). All financial companies must reduce the amount of non-performing loans (Ongore and Kusa, 2013). A low impairment assets to total assets ratio shows that a bank portfolio is healthy and performing well (Sangmi and Tabassum, 2010). This study uses the impairment asset to total asset ratio and the provision of doubtful debt to gross loans and advances to measure asset quality.

Management Efficiency (M)

Management efficiency is a key indicator of financial health. It is typically measured using non-interest expenses to total income, personnel expenses to average assets, and cost to income ratio (Boyacioglu et al., 2009; Cihak and Poghosyan, 2009; Oshinsky and Olin, 2006). Management quality is difficult to measure. Managing operating expenses efficiently is another element which reflects management quality (DeYoung, 1998). The efficiency of operating cost is measured using the cost income ratio, defined as operating expenses to operating income (Mathuva, 2009). Hess and Francis (2004) note that there is a reverse relationship between the cost income ratio and bank profitability. Gosh, Narain, and Sahoo (2003) also declares that there is a negative relation between efficiency and the cost income ratio.

The second ratio used in this study for evaluating management efficiency is used by Jaikengkit (2004). He uses operating expenses to total assets, as he believes this ratio captures management efficiency. He explains that a higher ratio reflects lower management quality and a higher risk of failure. The rationale here is that a well-managed bank is able to use resources more efficiently than poorly managed banks. Thus, the current study uses the cost income ratio and operating expenses to total assets to account for management efficiency.

Earnings (E)

Grier (2007) noted that a stable profit not only provides assurance for investors but also enables a bank to absorb loan losses and ensure sufficient funds are available. Constant healthy profits are vital to financial institutions' sustainability. The profitability or earnings ratio evaluates an entity's ability to produce profit utilising assets at their disposal (Dang, 2011; Ongore and Kusa, 2013). It is normally calculated by net income or interest income divided by total assets and demonstrates management's ability to generate income from a company's resources (Khrawish, 2011). These two ratios are frequently used to measure earnings quality and have a reverse relationship with failure (Avkiran and Cai, 2012). A high return on assets indicates that the entity's efficiency is high and that it has a lower risk of failure (Jaikengkit, 2004). As with the prior literature (Boyacioglu et al., 2009; Canbas et al., 2005; Lanine and Vennet, 2006; Martin, 1977; Shumway, 2001; Wheelock and Wilson, 2000) this study uses net profit after tax to total assets and net interest to total assets as proxies for measuring earnings quality.

Liquidity (L)

Financial institutions make money by borrowing short term deposits at a lower interest rate than they charge to long-term borrowers. The gap between interest rates and the lending time leads to insufficient liquidity risks. Management should ensure that the institution retains adequate liquidity levels to meet its financial commitments, particularly to depositors. In addition, they should be able to quickly convert assets to cash with minimal loss (Dang, 2011). Liquidity is thus another indicator for a financial companies' performance. Rudolf (2009) notes that "the liquidity expresses the degree to which a bank is capable of fulfilling its respective obligations" (p.2).

Liquidity ratios indicate the portion of liquid assets that can be converted to cash over a year without an undue loss. However, scholars use different ratios to measure liquidity risk. Wheelock and Wilson (2000) consider liquidity with net purchases of federal funds divided by total assets, while Canbas et al. (2005) applied liquid assets to total assets as a proxy for liquidity. Distinguin et al. (2006) use the liquid assets to total deposits and borrowings as a proxy for measuring liquidity, while Douglas et al. (2014) use net operating cash flow to total assets. Dang (2011) reveals that liquidity is positively related to bank profitability. However, a study of financial institutions in China and Malaysia found no relationship between liquidity and bank performance (Said and Mohd, 2011). This study uses current assets to total assets and net operating cash flow to total assets as proxies for liquidity.

Size (S)

"S" in CAMELS refers to 'sensitivity to market risk.' Most scholars ignore this factor (see, for example, Wheelock and Wilson, 2000; Oshinsky and Olin, 2006; Distinguin et al., 2006; Ajiboye and Ilori, 2016). Boyacioglu et al. (2009) consider sensitivity to market risk in their study and measure it using trading securities to total assets, foreign assets to foreign liabilities, and net interest income to average asset. This study could not take those variables into account due to a lack of data. Alternatively, this study uses size, measured by total asset. Wheelock and Wilson (2000), Lanine and Vennet (2006), and Kato and Hagendorff (2010) demonstrate that size is negatively related to the failure. This reverse relation can be explained by the 'too big to fail' view and the expansion effect (Curry et al., 2003; Hagendorff and Kato, 2010). Thus, total assets are used as a proxy for size.

Agency-related Variables

Corporate governance plays a central role in monitoring managers' behaviour and protecting shareholders. The foundation of the corporate governance system is to address the agency issues. The central control mechanism of corporate governance is to monitor board of directors and managers' behaviours effectively and protect shareholders from any conflict of interest. Both

Morin and Jarrell (2001) and Monks and Minow (2001) explain that corporate governance is effective oversight of the directors at board level. This oversight helps to provide a structure that protects and controls the relevant parties in the market. Guo (2011) and Wellalage (2012) emphasise that corporate governance advances company accountability and transparency and significantly enhances financial performance. This study includes additional Agency-related information as this has been identified as a key factor in company failure (Douglas et al., 2014; Harris, 2009).

Board Composition

Board composition considered to be an important factor in ensuring managerial performance. Two crucial elements are board size and director turnover. The number of directors on the board can directly impact upon efficiency and consequently corporate performance. Some studies suggest that larger boards have a negative influence and tend to be less efficient than smaller boards. They believe it is difficult to arrange board meeting and reach consensus, which is believed to result in slow and inefficient decision making (Hartarska and Nadolnyak, 2007). However, some scholars contend that larger boards have a positive effect on firm performance. A greater number of board members leads to strategic decisions and reduces the likelihood of CEO dominance. Agrawal and Mandelker (2009) argue that larger boards mean more experience. Coles, Daniel and Naveen (2008) found that CEOs of firms with high debt require boards with greater levels of expertise. Board size is the first variable in this study for board composition.

Institutional performance and how directors react to that is an important element. If directors have a self-interested character, they may consider the reputational and legal costs of being a director of a distressed or failing company (Fama, 1980). In this situation, they may prefer to resign or leave the company before their reputation is tarnished or they lose too many board members. Hubbard and Kosnik (1997) found that director turnover was notably higher in bankrupt banks during the 1980s, particularly during the Texas savings and loan crisis. Srinivasan (2005) studied 409 companies from 1997 to 2001 that restated their earnings and showed that director turnover was 14% in the three years before restating earnings and 48% after restating downward. This study considers the number of directors appointed or resigned as proxies for director turnover.

Related Party Transactions

In many countries, financial institutions are managed by directors or managers which are considerably interest in non-financial companies. This means that a notable portion of lending is directed toward their related parties. Faccio, Lang, and Young (2001) state that in Asia, shareholders (who constitute nearly 60 percent of trading companies) control a bank. This figure is around 28% in Europe. La Porta et al.'s (2003) study on 17 Mexican banks in 1995 found that related lending accounts for nearly 20% of commercial loans and have better loan conditions than unrelated loans, like interest rate is 4% lower than normal. They prove related party loans have 33% more possibility of failing. Beatson (2009) notes that transactions among related parties in New Zealand are often extremely high and that institutional funds were used to benefit the shareholders (like lending them excessive amounts of money, even when there was a low likelihood of repayment). Bhuiyan and Roudaki (2018) also found that almost half of the failed New Zealand finance companies were engaged in related party transactions. This study follows Douglas et al. (2014) and uses related party lending to total asset and related party lending to total loan and advances as proxies for related party transactions.

Audit

The audit plays a critical role in ensuring the quality of financial statements, including the issue of going-concern opinions (Douglas et al., 2014). Audit modification acts as an early warning of financial problems. Auditors are responsible for issuing going-concern reports if there is concern about a company's ability to continue over time (not more than 12 months). They have to issue a going-concern report which must state that a company is under financial distress (Holder-Webb and Cohen, 2007). Carson et al. (2013) found that more than 60% of bankruptcies are followed by reported going concern uncertainties. However, Francis and Yu (2009) declare that large auditors like Big 4 are more likely to issue going-concern reports. As a proxy for audit modification, the dummy variable "1" was used to indicate annual reports with qualified audit report or where there was "fundamental uncertainty" or "emphasis of matter" noted in the audit report even though the auditor issued an unqualified audit report, otherwise "0".

Palmrose (1988) discusses the litigation cost of audit failures for auditors. High quality auditors try to avoid this cost because it represents a loss of reputation as well. Khurana and Raman (2004) note that litigation penalties motivate the Big 4 auditors in the United States to provide high quality audits. In addition, the Big 4 have a more conservative policy (Sarbanes-Oxley Act of 2002) regarding accepting and retaining clients (Rama and Read, 2006). In this study, a dummy variable "1" is used for companies that have a Big auditor. A "0" is used otherwise. The Big 4 includes Price Waterhouse Coopers, Deloitte, Ernst and Young and KPMG.

Prior studies have shown that there is a relationship between going-concern opinion and audit lags. Higher audit lags increase the possibility of going-concern opinions (DeFond et al., 2002; Geiger et al., 2005; Li, 2009). This delay could be either the result of doing more work to evaluate the company's ability to continue trading or uncovering financial problems. Audit lag is calculated by the number of days from the end of the financial year to the audit's sign off date.

On average, the Big 4 charge 20% more than the other audit companies (DeFond et al., 2000; Ferguson et al., 2003). However, Francis (2004) declares that a higher audit fee indicates better quality. The high fee either relates to more time allocated to the audit process or is an acknowledgement of the auditor's expertise. Although Carcello and Neal (2000) could not find any evidence that audit remuneration is related to company failure, we include the audit fee in our study to see if there is any relationship. This study uses audit modification, Big 4, audit lags and auditor remuneration to measure audit attitudes of failed and non-failed financial companies.

Trustees

As explain earlier corporate trustees are responsible for acting on behalf of all depositors and monitoring financial institutions in New Zealand. Davies (2007) explains that trustees have a "statutory whistle-blowing duty" and if they suspect that a financial company has breached its trust deed, it is their responsibility to inform the Registrar of Companies for further investigation. Most of the failed companies in New Zealand used three common trustee company to supervise them and their investors' interests (Yahanpath and Cavanagh, 2011). This study investigates to see if there is any relationship between these trustees and failure among financial companies.

Wilson et al. (2013) note that even if trustees are aware of any breach, they often agree to amend definitions in the trust deed, like changing the definition of related party transaction. The probability of trust deed amendment is higher near to the time of the failure. This study checks amended trust deeds and investigates whether amendment in trust deed is a predictor for failure.

Maturity

Studies prove that maturity or length of operation is linked to profitability (Strøm, D'Espallier, and Mersland, 2014). Navajas et al. (2000) explain that maturity builds borrower and market confidence. Caudill et al. (2009) note that a mature firm generally controls costs more efficiently rather than newer firms, which results in higher profitability. However, Kyereboah-Coleman and Osei (2008) conclude that older finance companies are more profitable, but that tend to focus on limited groups of clients. In addition, Nurmakhanova et al. (2015) declare that mature institutions serve fewer richer clients, with larger loans. Alternatively, (Mersland and Strøm, 2009, 2010) contend that the age of a firm has a direct relationship with the number of the active borrowers. Age or the number of years in the market is commonly used a proxy for measuring maturity (Hartarska, 2005; Marimuthu and Kolandaisamy, 2009; Mersland and Strøm, 2010; Microfinance

Information Exchange, 2007). This study uses age as a proxy for maturity by considering the difference between the incorporation date published on the Company Office's website and the year of failure.

Media

Media, as an extra-legal institution, plays a critical role in educating and influencing the public (Atanassov and Kim, 2009; Dyck and Zingales, 2004; Haw et al., 2004). For instance, El Ghoul et al. (2016) investigates the role of media in influencing corporations' engagement in corporate social responsibility (CSR) by using a large sample of 4,453 companies from 53 countries, from 2003 to 2012. They declare that the media has a strong ability to encourage companies to engage more in CSR activities, especially in countries with more freedom. Burgess (2010) and Sobel, Dutta and Roy (2011) all use the Freedom of the Press index to compare media freedom among countries. Cahan, Chen, Chen and Nguyen (2015) use annual scores of media favourability as a proxy for media. It is equal to the total number of positive news less negative news to total number of news items in a year. New Zealand is a small country with a limited number of media outlets, which cover all the news. This study uses the two of the major newspapers; the NZHerald and Stuff. They cover nearly 100% of the news all over the country. To collect the number of news, this study uses the Google search engine (www.google.com.nz), NZHerald and Stuff website search engine using the name of each company in quotation marks as search terms (Du et al., 2016). The total number of published news items was not significant enough to classify them as positive or negative news. However, this study computes the total number of published new items as a proxy for media. In short, it provides an overall view of whether media has any influence on failed financial companies.

External Factors/Macroeconomic Factors

There is a series of macroeconomic indicators available for analysis and they are typical time varying covariates. However, unlike firm-specific covariates, macroeconomic factors are variant in the period but not in the case. So for all companies existing in a period, we assume macroeconomic conditions have the same impact on them. Some researchers (e.g. Nam et al., 2008) use macroeconomic changes as the baseline hazard, and others (e.g. Carling et al., 2007) argue that macroeconomic conditions have a lagged impact on the real economy.

With reference to literature and professional opinions, we include four macroeconomic variables in the model. Gross Domestic Product (GDP), Inflation, Official Cash Rate (OCR) and House Price Interest Rate (HPI) are the macroeconomic variables that impact the performances of financial institutions.

GDP growth positively affects the demand and supply of banking services and improves banks' asset quality. Decreases in GDP, particularly during recession periods, lead to a deterioration of credit quality, which negatively affects bank efficiency. Adjei-Frimpong (2013) supports the positive impact of real GDP growth on financial companies' efficiency. However, Delis, Koutsomanoli-Fillipaki, Staikouras, and Katerina's (2009) study on South East European countries found a negative relation. Di Patti and Hardy (2005) concluded that there was no significant relation between GDP and bank efficiency among Pakistani banks.

Inflation rates increase costs and lessen cost efficiency. Kasman and Yildirim (2006) explain that as inflation grows, so do costs. This leads to a decrease in profits as banks tend to grow branch networks. However, Athanasoglou, Sophocles, and Matthaios (2005) contend that the relationship between inflation levels and bank profitability is not clear in the case of Greece (Vong and Chan, 2009). Simpasa (2010) declares that inflation rate is directly related to bank market power. As inflation rates grow, banks increase their product prices leading to higher market power.

The last two macroeconomic variables are the Official Cash Rate (OCR) and House Price Interest Rate (HPI). Delis and Kouretas (2011) analysed 18000 annual observations on the Euro zone and found that low interest rates increase bank risk-taking behaviour. However, they explain that the overall impact of interest rates on bank risk-taking depends on a bank's capital. Individual bank features disclose that the interest rate has less effect on risky assets for banks with higher equity capital and has a higher impact on banks with higher off-balance sheet items. Additionally, several scholars (Borio and Zhu, 2008; Dell' Ariccia and Marquez, 2006; Rajan, 2006) note that banks appear to increase risk-taking behaviour during the low-interest rate periods. Kanwal and Nadeem (2013) found a significant positive relationship between interest rates with the profitability of public commercial banks in Pakistan between 2001 and 2011. Significantly, the Reserve Bank of New Zealand announces both the OCR and HPI and their changes parallel to each other.

4.4 Data Analysis

After explaining all the variable measurements, this section describes the research models used to test the relationship between CAMELS, Agency-related variables and financial Institution failure. Two methods were chosen to test the data in order to identify the most suitable model for prediction. These are the logistic regression model and the hazard model.

4.4.1 Logistic Regression

David Cox first introduced logistic regression in 1958. He argued that a binary response of success "1" or failure "0" depended on the character of one or some of the preassigned independent variables. Since then logistic regression has been used in different areas like social sciences (Chuang, 1997; Tolman and Weisz, 1995) and higher educational research (Cabrera, 1994; Peng, So, Stage, and St. John, 2002). In 1977 Martin used logistic regression to build an early warning model for predicting future failures. Today, logistic regression is seen as one of the best models for bank failure prediction (Kim, 2011; Li, 2014; Lin and McClean, 2001). The first advantage of logit models, in comparison with OLS and probit models, is that it does not impose the assumption of normality on the independent variable. Logit models also provide probabilistic output meaning that results do not need to be converted into the probabilistic measure, which may cause further errors (Ohlson, 1980). Jagtiani, Kolari, Lemieux, and Shin (2003) argue that simple logit models often provide better results than some of the complex models with the same data. It is for these reasons that the logistic regression model is the first one used in this study.

Logistic regression or the logit model is a classic model in failure prediction. It is capable of dealing with binary response variables when individuals are assigned to one of two classes (like good or bad or fail or not fail). Logistic models presume that for any company with a specific set of features, there is a chance of failure. Therefore, the probability of failure depends conditionally on these features. This can be indicated by the equation below:

$$D_i^* = \beta x_i + \beta_0 \tag{1}$$

Where

$$D_i = 1 \qquad \text{if } D_i^* \geq 0$$

$$D_i = 0 \qquad \text{otherwise,}$$

Where β is the vector of unknown parameters, x_i is a set of features used to ascertain a potential failure $(D_i = 1)$ and β_0 denotes the error term (Duda and Schmidt, 2010).

In logistic regression, the value of dependent variables is limited to (0, 1) compared with linear regression where the value can go from -∞ to +∞. A standard logistic distribution function is $f(x) = \frac{1}{1+e^{-x}}$ which has a sigmoid shape on the coordinate (Figure 4.1).

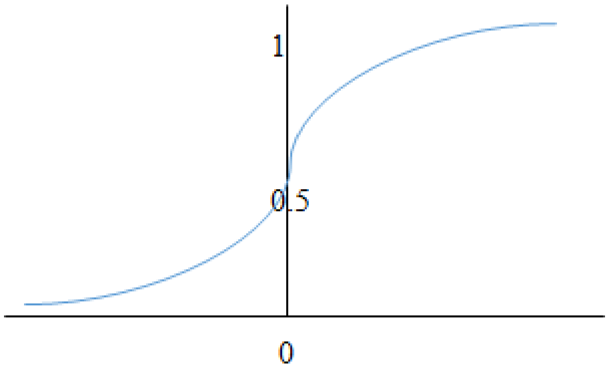

Figure 4-1 Distribution of Logistic Regression

The normal distribution is not required in binary logistic regression. While the dependent variable is categorical, the independent variables can either be continuous or categorical variables. In failure prediction, the probability of default depends on a group of explanatory variables which are expressed as (Cox, 1958) :

$$P(D = 1 \mid x1, x2, \ldots, xk) = \frac{1}{1 + e^{-(\beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta kxk)}} \quad (2)$$

Where $P(D = 1)$ the probability of failure, β is the vector of unknown parameters, k is the number of explanatory variables and x is the institution characteristics.

When P_i represent the probability of default for company i, the equation could be re-written as

$$\frac{1 - p_i}{p_i} = e^{-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik})} \quad (3)$$

Then logarithms of both sides of the equation, have (Christensen, 1997- P. 55)

$$\log(\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \quad (4)$$

If logit (P) represents the short for $\log(\frac{p_i}{1-p_i})$ and vectors β, x to represent $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ and $x_{i1}, x_{i2}, \ldots, x_{ik}$, we have

$$\text{logit } (p_i) = \beta x^T \quad (5)$$

When p_i take values from 0 to 1, $\frac{p_i}{1-p_i}$ take values from 0 to ∞ and logit (p_i) values from -∞ to +∞, as linear regression (Li, 2014).

In failure prediction studies, researchers have followed different variable classification; and the results have been inconsistent or even controversial, particularly regarding the issue of which variables, and to what degree these variables are associated with the probability of failure (Chen, Wang, and Wu, 2010; Han, 2012; Lakshana and Wijekoon, 2012). Some scholars (Chen et al., 2010; Fich and Slezak, 2008; Lee and Yeh, 2004) argue that the integration of corporate governance measures with financial variables improves prediction accuracy. This study predicts the probability of failure by using new variables. Including as many variables as possible may increase predictive accuracy because more information is added. However, it is not practical to do so, and it may lead to the problem of overfitting (Li, 2014). Therefore, although a large collection of variables are available, this study groups the variables into financial and non-financial variables. The models are based on three different variable categories. The first model incorporates only CAMELS financial variables. The second model uses only Agency-related variables and the third model integrates both CAMELS and non-financial variables.

The first logistic regression model is as follows:

$$Failure_i = \beta_0 + \beta_1 CA_i + \beta_2 AQ_i + \beta_3 MC_i + \beta_4 EARN_i + \beta_5 LIQ_i + \beta_6 Size_i \qquad \text{(Model 1)}$$

In the case of financial institution i, $failure_i$ is represented by 1 when failure occurs and 0 otherwise. The independent variables include capital adequacy (CA_i), asset quality (AQ_i), management competency (MC_i), earnings ($EARN_i$), liquidity (LIQ_i) and firm size ($Size_i$) which are all CAMELS components. The related proxies for each variable were explained in detail in the previous sections.

The next model focuses solely on Agency-related variables:

$$Failure_i = \beta_0 + \beta_1 DIRCOMP_i + \beta_2 RP_i + \beta_3 AUD_i + \beta_4 TRUSTEE_i + \beta_5 FM_i + \beta_6 MEDIA_i \qquad \text{(Model 2)}$$

Where, for sample firm i, independent variables in this model consist of director compositions ($DIRCOMP_i$), related party transactions (RP_i), audit characteristics (AUD_i), trustee ($TRUSTEE_i$), firm maturity (FM_i) and media ($MEDIA_i$). The allocated proxies for pointed variables are described earlier.

The third model amalgamates CAMELS and Agency-related variables:

$$Failure_i = \beta_0 + \beta_1 CA_i + \beta_2 AQ_i + \beta_3 MC_i + \beta_4 EARN_i + \beta_5 LIQ_i + \beta_6 Size_i + \beta_7 DIRCOMP_i + \beta_8 RP_i + \beta_9 AUD_i + \beta_{10} TRUSTEE_i + \beta_{11} FM_i + \beta_{12} MEDIA_i \qquad \text{(Model 3)}$$

Where all of the variables are defined as above.

Each one of these three models is extended to three sub-models based on time intervention. In the sub-models T1, T2, and T3 are one year, two years, or three years before failure. Model 1 is extended as follow:

- Model 1-1: Using CAMELS variables in time “T1”
- Model 1-2: Using CAMELS variables in time “T2”
- Model 1-3: Using CAMELS variables in time “T3”

Model 2 is developed as outlined below:

- Model 2-1: Using Agency-related variables in time “T1”
- Model 2-2: Using Agency-related variables in time “T2”
- Model 2-3: Using Agency-related variables in time “T3”

The following sub-models are established based on Model 3:

- Model 3-1: Using CAMELS and Agency-related variables in time “T1”
- Model 3-2: Using CAMELS and Agency-related variables in time “T2”
- Model 3-3: Using CAMELS and Agency-related variables in time “T3”

The four macroeconomic variables of GDP, Inflation, OCR and HPI are entered in all the models as control variables. These variables are constant for the year, however may vary from year to year within the model. As explained earlier, t donates the year a company fails and t-1 is the year before failure. For example, if a company fails in 2009, the t-1 is 2008 and if a company fails in 2007, the t-1 is 2006. Therefore, the t-1 varies from company to company and this may result in a macroeconomic value that differs for each company, as the year of failure is different.

4.4.2 Hazard Model

As with other static models (with the exception of multi-period models), logistic regression is a cross-sectional model. This model can only predict the probability of failure at a given time (like in this study, one, two or three years before failure). However, this model does not address the fact that at this given time, some ‘healthy’ institutions will ultimately fail. To address this problem, Shumway (2001) proposed hazard models. These models have gained popularity in credit risk prediction fields (see for example Bennett, Kimmel, and Thornton, 2016; Cox, Kimmel, and Wang, 2017).

Hazard models have three main advantages. Firstly, the models can be modified during risk periods by using a function of time of being financially healthy which is called survival time.

Shumway (2001) explains that a company has its life cycle, like a human being, and its own death risk, over its life time. Hazard models incorporate this risk.

In addition, hazard models can naturally incorporate Time-Varying Covariates (TVC) which are defined as explanatory variables which change over time. Macroeconomic variables are another group of TVCs which are associated with business failure (discussed in the Basel II framework and addressed by Wilson and Altanlar, 2014). Macroeconomic indicators are published quarterly or yearly. These can be easily included in discrete hazard models.

Finally, hazard models result in better predictions, as models use more data. This is in contrast to cross-sectional models which only consider a single period of data. Hazard models can include data over a period of time (this is commonly referred to as panel data). This study uses three years of data. Observing data over an extended period of times means that the training sample is larger and hence, parameter estimates are more robust over time.

It is for these reasons that this study uses a discrete-time hazard model. This model is a type of survival model, in which covariates are related to the time that passes before bankruptcy happens. The survival function and hazard model function are based on Rodríguez's (2010) work:

The continuous time before failure of a company is recognised as survival time and is denoted as t. The density function of variable t is $f(t_i, x_i, \beta) = f(t)$ and its cumulative density function is $F(t_i, x_i, \beta) = F(t) = \Pr(T \leq t)$; where β represents a vector of parameters and x represents a vector of financial institution characteristic which are CAMELS variables and Agency-related variables and T is the duration before failure. The probability that a company survives beyond time t is expressed by the survival function, $S(t_i, x_i, \beta) = S(t)$:

$$S(t) = 1 - \sum f(t) = 1 - F(t) = \Pr(T > t) \tag{6}$$

In addition, the hazard function $h(t_i, x_i, \beta) = h(t)$ is the event rate at time t conditional on survival until time t or later. In other words, the hazard function is the ratio of the probability density function $f(t)$ to the survival function $S(t)$:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{S(t)} = \frac{S'(t)}{S(t)} \tag{7}$$

The hazard rate is the constant probability of failure. It means that a company can survive until time t and has a possibility of failing in a small period of time (Δt). However, the hazard rate might be seen as the immediate risk of default (Nam et al., 2008). Therefore, the hazard rate can range from 0 to ∞. The cumulative hazard function measures the accumulated total risk up to time t is:

$$H(t) = \int_{0}^{t} h(t)dt = -\int_{0}^{t} \frac{S'(t)}{S(t)} dt = -\ln[S(t)] \tag{8}$$

Therefore:

$$S(t) = \exp\left[-\int_{0}^{t} h(t)dt\right] \tag{9}$$

$$F(t) = 1 - \exp\left[-\int_{0}^{t} h(t)dt\right] \tag{10}$$

$$f(t) = h(t)\exp\left[-\int_{0}^{t} h(t)dt\right] \tag{11}$$

For a continuous hazard model, some common distributions can be used for $h(t)$ like exponential, Weibull, lognormal, log-logistic and Gomperts-Makeham distributions. Cox and Oakes (1984) suggest that the semi-parametric proportional regression to evaluate the β by presuming the proportional hazard remain the same.

$$h(t, x(t), \beta) = h_0(x)\exp(\beta^T x) \tag{12}$$

Here h_0 is the baseline hazard and β is the vector of parameters affecting the time-varying covariate $x(t)$.

In discrete time hazard models, the failure can only happen in a period of time t. The survival equation and hazard equation are a bit different (Cox and Oakes, 1984):

$$S(t, x; \beta) = \prod_{j<t_i} [1 - h(j, x; \beta)] \tag{13}$$

The likelihood function of the discrete-time hazard model is:

$$l = \prod_{i=1}^{n} (h(t_i, x_i; \beta) \prod_{j<t_i} [1 - h(j, x; \beta)]) \tag{14}$$

Hence the log-likelihood function of that (Allison, 1982) is

$$\log l = \sum_{i=1}^{n} y_{i,t_i} \log\left[\frac{h(t_i, x_{i,t_i}; \beta)}{1 - h((t_i, x_{i,t_i}; \beta)}\right] + \sum_{i=1}^{n}\sum_{j=1}^{t_i} \log[1 - h(j, x_{i,j}; \beta)] \tag{15}$$

Where y_{i,t_i}=1 if company i experiences failure in period t_i , 0 otherwise.

Therefore, a discrete-time hazard model, as explained above, can be estimated using a logit model with proper adjustment to the test statistics (Nam et al., 2008).

$$\Pr(y_{i,t} = 1 | x_{i,t}) = h(t, x_{i,t}; \beta) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 h_0(t) + \beta^T x_{i,t})]} \tag{16}$$

In the logit model, test statistics presume that the bank-years are independent observations. However, in discrete-time hazard models, the firm-year observations of a particular institution cannot be independent because a firm cannot fail in period T if it failed in period T-1; and if an institution survives to period T, it cannot have failed in period T-1. Therefore, each bank's life span only makes one observation for the hazard model (Cole and Wu, 2009).

Shumway (2001) notes that the likelihood function of the multi-period logit model is equal to a discrete-time hazard model with a hazard rate $h(0) = F(t_i, x_i, \beta)$, which takes the same form as the cumulative probability function of a logit model. Hence, hazard models can be simply approximated by using the logistic regression technique. Additionally, the model also allows for the incorporation of macroeconomic dependencies. Separating β into $\beta 1$ and $\beta 2$ creates the following form of the hazard function and assists with understanding how to incorporate macroeconomic dependencies. This study uses a duration model with time-varying covariates and macro-economic dependencies:

$$h(0) = F(0) = \frac{1}{1 + exp[-(\beta'_1 k_t + \beta'_2 x_i)]} \tag{17}$$

In this equation, the hazard rate consists of a time-dependent k_t, which is also known as a baseline hazard function and denotes a macroeconomic variable. Possible macroeconomic variables include the OCR, GDP, inflation and HPI in that period. The second part of the hazard function, $\beta'_2 x_i$, is a function of firm specific characteristics represented by financial ratios and non-financial indexes, the same as those which are explained under logistic regression models.

This model also shares similarities with the logit model in that it is built on three different variable categories. As noted, the first model uses only CAMELS financial variables. The second model incorporates only Agency-related variables, and the third model integrates both CAMELS and non-financial variables.

As explained earlier, firm-year observations of an institution are not independent, because a firm cannot fail in period T if it failed in period T-1. As with the logistic model, this model assesses the three consecutive years before failure occurs.

The models used in this study are as follows:

The Logit model

Model 1: Using CAMELS variables

- Model 1-1: Using CAMELS variables in time "T1"
- Model 1-2: Using CAMELS variables in time "T2"
- Model 1-3: Using CAMELS variables in time "T3"

Model 2: Using Agency-related variables

- Model 2-1: Using Agency-related variables in time "T1"
- Model 2-2: Using Agency-related variables in time "T2"
- Model 2-3: Using Agency-related variables in time "T3"

Model 3: Using CAMELS and Agency-related variables

- Model 3-1: Using CAMELS and Agency-related variables in time "T1"
- Model 3-2: Using CAMELS and Agency-related variables in time "T2"
- Model 3-3: Using CAMELS and Agency-related variables in time "T3"

The Hazard model

- Model 4: Using CAMELS variables on the combination of "T1, T2 and T3"
- Model 5: Using Agency-related variables on the combination of "T1, T2 and T3"
- Model 6: Using CAMELS and Agency-related variables on the combination of "T1, T2 and T3"

4.5 Cut-off Score

There are many different ways to evaluate the performance of a model. However, a model is typically assessed by its classification accuracy and discriminant power. In regards to classification accuracy, when the likelihood of a default is predicted by a model, a cut-off score is normally allocated to the series of probabilities. The typical cut-off score is 0.50. Following prior studies

(Jaikengkit, 2004; Li, 2014), this study uses 0.50 as a cut-off score. This means that financial institutions with possibilities above the cut-off point are categorised as 'failed' while those with possibilities below the cut-off point are seen as 'healthy' ones with a lower chance of default.

4.6 Model Validation

A prediction model must also include validation tests to ensure that the results are valid both in the sample and post-sample periods. Both Fuertes and Kalotychou (2006) and Rodriguez and Rodriguez (2006) suggest that compound models provide more accurate predictions when tested in-sample. Fantazzini and Figini (2009) also found superior out-of-sample predictions from simple logit models as opposed to more advanced models in their study of credit risk default among Small Medium Enterprises. Validation tests would typically be conducted using holdout samples. The developed model (that is built from in-sample data), is usually tested for validity using the out-of-sample. This technique protects against the upward bias that might occur if the sample used for the developing model was the same as the sample used for validating the model (Jaikengkit, 2004). This study examines the accuracy of the models by testing the out-of-sample data. The out-of-sample data was collected from failed financial institutions (after 2010), after the implementation of new regulations.

4.6.1 Measuring Model Validity

A statistically significant covariate does not mean that predictive performance is improved if the variable is incorporated into a model. The performance of a model can be measured by its classification accuracy. When measuring the classification accuracy of a model, a cut-off point is typically allocated to a series of probabilities. Then, institutions with probabilities above the cut-off point are considered as 'failed', and those with probabilities below the cut-off point are considered to be 'healthy' with a lower chance of failure. The cut-off point is vital for evaluators; while one may prefer to concentrate on good classifications, someone else may consider whether all defaults have been discovered (Li, 2014). In this study, Type I and Type II errors are calculated failed and healthy classifications using a cut-off point of 0.5. The Type I error occurs when the null hypothesis (H0) is true but is rejected. A Type II error occurs when the null hypothesis (H0) is accepted when it is false (Sheskin, 2003). In this study, a Type I error occurs when a healthy institution is misclassified as a failed institution. A Type II error occurs when a failed institution is misclassified as a healthy institution. Therefore, Type I and Type II errors are usually called false positive and false negative respectively. Their relationship is described in Table 4.4.

Table 4-4 Classification Matrix

		Observation	
		Healthy	**Failed**
Prediction	**Healthy predicted**	**Correct Healthy** True positive	**Type II error** False negative
	Failed predicted	**Type I error** False positive	**Correct Failed** True negative

Therefore, the cut-off point splits into four different areas: true Healthy (H_H), false Healthy (F_H), true Failed (F_F) and false Failed (H_F).

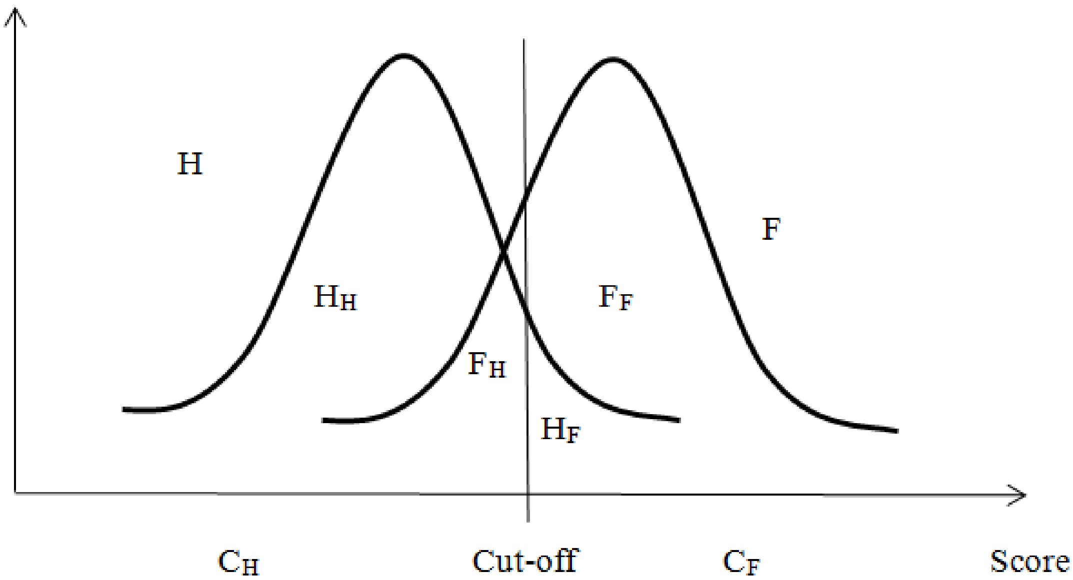

Figure 4-2 Type I and Type II Errors

More noticeably, in Figure 4-2, if curves H and F demonstrate the distribution of "Healthies" and "Fails" and the x axis is the predicted score, it is obvious that areas under the curves overlap in the middle. When the cut-off point is identified, the classification of "Healthies" and "Fails" can be ascertained, as C_H and C_F. Then,

$$\text{Type I error rate} = \frac{H_F}{H_F + F_F} * 100\% \tag{18}$$

$$\text{Type II error rate} = \frac{\mathrm{F_H}}{\mathrm{H_H} + \mathrm{F_H}} * 100\% \tag{19}$$

And

$$\text{Overall accuracy rate} = \frac{H_H + F_F}{H_H + H_F + F_F + F_H} * 100\% \tag{20}$$

Obviously it is better to have lower Type I and Type II error rates and a higher overall accuracy rate for good predictive performance. However, Type I and Type II errors are measured solely for a single cut-off point. It is a crucial weakness of the error rate that the predictive accuracy of the model depends on the cut-off point chosen. Therefore, evaluating the discriminant power of a model determines not only the group of cases but also define the distance of how good a non-default case is and how bad a default case is (Li, 2014). Hence, Receiver Operation Curve (ROC) provides a summary measure for the overall performance of all possible cut-offs (Crook, Edelman, and Thomas, 2007). The ROC curve is a plot which shows the true positive rate against the false positive rate since all possible cut-off values are considered. The true positive rate is called sensitivity while the false positive rate is called 1-specificity, whereas specificity is the true negative rate.

If the distribution of the two groups (Healthy and Failed) is totally separated by a model, all of the fails would be correctly classified, before any of the healthy ones are misclassified. In this instance, the ROC curve will lie over the edges of the square OBC in Figure 4-3. If there is no separation at all, the performance of a model will equal a random guess; the ROC curve will be the diagonal line OAC (Crook et al., 2007). The measure of overall performance in the ROC graph is the Area Under ROC (AUC), which is the area of OECF. Although AUC is a commonly used measure of performance for classification, it is a single number resulted from a classification rule and has a well-known weakness. The AUC can give potentially misleading results if ROC curves cross (Hand, 2009). When this happens, there is a chance that one cross curve has a larger AUC even though another model shows better performance over the entire range of values. The Gini (1909) coefficient is more informative than AUC since the curve may cross. The Gini coefficient is defined as the proportion of the area between OEC and the diagonal line in the half square, as outlined below:

$$Gini = \frac{A_{OEC}}{A_{OBC}} = \frac{0.5 - A_{OBCE}}{0.5} = \frac{0.5-(1-A_{OECF})}{0.5} = \frac{A_{\,OECF}-0.5}{0.5} = 2\,A_{OECF} - 1 \tag{21}$$

Where $A_{OECF} = \int_0^1 L(x)dx$

Therefore, the relationship between AUC and Gini is

$$\text{Gini} = 2\text{AUC} - 1 \tag{22}$$

By doubling the AUC value, the Gini coefficient resolves any misleading results due to crossed curves (Hand, 2009).

One more related measures of separation illustrated in Figure 4-3 is the Kolmogorov-Smirnov (KS) statistic, which is the maximum difference between the bad and good cumulative score distribution. $F(s|H)$ indicates the probability that a good has a score less than s and correspondingly for bad as $F(s|F)$. The KS is the maximum difference between $F(s|H)$ and $F(s|F)$ at any score. KS demonstrates what is the maximum difference between the probability that a case is good and is rejected and the probability one is bad and is rejected.

Figure 4-3 is the plot of $F(s|H)$(x axis) against $F(s|F)$ (y axis). The Ks is the maximum distance between $F(s|H)$ and $F(s|F)$:

$$\mathrm{KS} = max|F(s|F) - F(s|H)| \tag{23}$$

On the plot AD = OD, thus,

$$\mathrm{KS} = max|ED - OD| \tag{24}$$

$$\mathrm{KS} = max|EA + AD - OD| \tag{25}$$

$$\mathrm{KS} = max|EA| \tag{26}$$

KS becomes the largest vertical distance from the curve to diagonal.

Hand (2005) declares that the main constraint of AUC, Gini and KS is that they only consider the number of misclassified cases but do not take into account the cost of misclassification. In reality, the investor has a different view of the classifications (Fail and Healthy), particularly when considering the costs associated with misclassification. Misclassification of a Healthy to be a Fail

means that an investor might lose profits that could be generated by investing in that particular company (Bellovary, Giacomino, and Akers, 2007). Misclassification of a Fail as a Healthy might cause the investor to lose a huge amount of capital. Hand (2009) introduces the H measure if the cost distributions are known. However, if the costs are unidentified, the preference is still to compare the H measure of models as it is assumed that the cost weight function is the same in its estimation, which makes them comparable (Li, 2014). As with other performance measures, the discriminative power is better when the H value is larger.

The error table, AUC, Gini, KS and H measure are all used to assess the model's performance.

By running the Logit model and Hazard model for each company year, the SPSS software generates a probability amount as one of the model output. In the next stage, the probability amount (classifier score) uses as the input for measuring the discriminative power.

The four measures of predictive accuracy (AUC, Gini, KS and H measure) are all calculated using Hand and Anagnostopoulos' (2013) R code in the R environment.

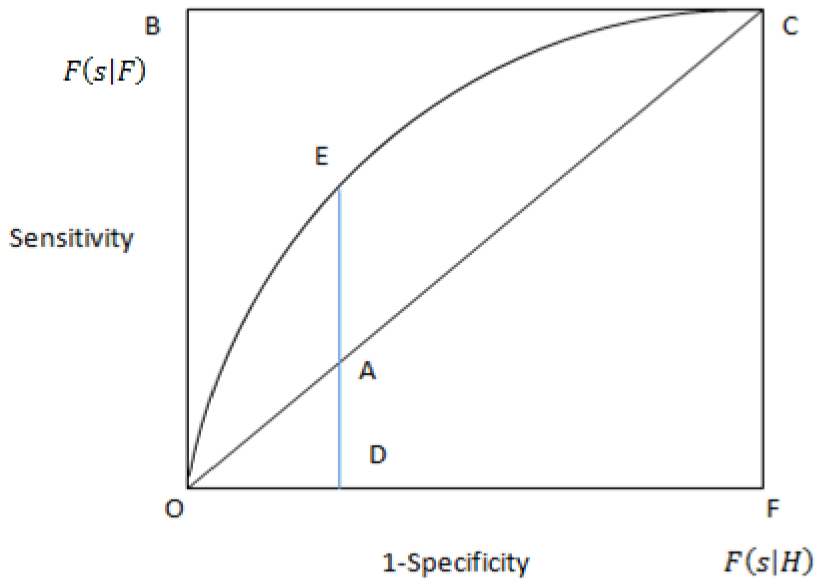

Figure 4-3 ROC, Gini and KS

4.7 Summary

This chapter has detailed this study's research methods. First, it has outlined the sample and data collection methods as well as the sample size. The final sample was 35 failed and 35 healthy financial institutions. It has also provided a detailed summary of all the variable measurements which were used. It has explained the reasons behind choosing the two models; the logit model and the hazard model. The final section has described the cut-off scores and model validations that are used to ensure accuracy and the performance of prediction models. These include Type I, Type II, overall accuracy, AUC, Gini, KS and H. Having detailed the study's methods; the following chapter presents the results.

Chapter 5

Data Analysis and Findings

5.1 Introduction

Having provided the research methodology of this study, Chapter 5 presents the study's main findings. It begins with a review of the data cleaning process and methodology around missing data, which is part of the data preparation process. The next section focuses on the descriptive and univariate analysis of all the variables. This is followed by the interpretation of the results obtained from the correlation matrix analysis. It then explains the logistic regression and hazard model results before moving on to consider model accuracy and interpretation of the results. The conclusion identifies key findings.

5.2 Data Mining

Data preparation is fundamental to data analysis. As there may be a few low-quality values in data sources which can significantly affect the results, data must first go through a pre-treatment process. Outliers and missing data are two common problems that may arise in the process of data collection.

Outliers refer to values that are abnormal when compared to other values in the overall distribution of variables. When the value of a collected data does not fit into the normal distribution, it is considered to be an outlier. In a pattern of variable distribution, outliers lie far away from the majority of other data points. The existence of these outliers in data sample brings bias into statistical estimates; for example, mean values result in under or over-estimated results (Kwak and Kim, 2017). Therefore, dealing with outliers is necessary before one begins the data analysis. The process of data cleaning comprises of amending outliers or substituting values after identifying their source.

In some cases, the models are run with and without outliers to see if the results are significantly affected. On the condition that the results are not significantly influenced, the outliers are kept in the sample (as the sample size is already small enough without removing companies due to one or two outliers). The process of data mining is explained in the next section.

5.3 Missing Data

Missing data is common in social science research (Patrician, 2002; Puma, Olsen, Bell, and Price, 2009). This study is no exception. Rubin (1976) defined three types of missing data; missing completely at random, missing at random, missing not at random. Missing data may affect model outcomes. If the possibility of missing data is not related to any other variable in the data set or the value of the observation, it is missing completely at random data; the data is missing at random if it results from missing values of another variable in the data set (Allison, 2001). The third type, missing not at random, is when there is no secondary variable available to explain it (Muthen and Muthen, 2004). There are different techniques to handle missing data depending on the nature of the data and missing data patterns. The most common technique is listwise deletion. This method deletes cases with missing data and runs the analysis using the remaining data. This method works well with missing completely at random data and results in unbiased parameter estimates (Allison, 2001). However, when the missing data is from the other two types or the sample size is too small, listwise deletion may lead to biased results, since the remaining cases may not be representative of the full sample (Von Hippel, 2004). In order to prevent losing cases in small samples, Rubin's 1976 multiple imputation technique introduces a reasonable value for each missing cell. This method generates multiple sets of new data for imputed values, which are different from set to set. This repeating imputation for multiple times solves the problem of underestimating standard errors (Rubin, 1976). Each dataset is analysed separately, with outcomes pooled for ultimate inferences. The practice of several imputations and combined results lead to a more precise analysis. It resolves the uncertainty about the actual value of the missing data.

In this study, missing data is classified as missing not at random, as the data is not included in the financial statements. Most of the missing data relate to not classified assets to current and non-current assets for measuring liquidity risks and not having cash flow reports for evaluating management efficiency. As the missing data is type three and the sample size is small, this study uses the multiple imputation method to handle missing data. SPSS runs multiple imputation techniques automatically (five times), which results in five different sets of data for each piece of missing data. The average of these five figures is the output which replaces the missing figure in the data sheet. However, if the final calculated data for the current asset to total asset is more than one, then the figure is manually corrected to the maximum possible amount, which is equal to one.

5.4 Descriptive Statistics Results

In order to obtain a greater understanding of the data's characteristics, this study uses descriptive analysis. Table 5.1 depicts all of the study's independent variables. These are classified according to CAMELS and Agency-related variables. There are 14 CAMELS variables and 14 Agency-related variables. A Skewness score between -2 and +2 and a Kurtosis score between -4 and +4, are considered normal distributions of the variables.

The descriptive analysis was run for failed and non-failed companies for each year separately, covering the first, second and third year before failure. As presented in Table 5-1, the mean value (Mean) of board size (NUMDIR) is 4.24 at t-1 and 4.40 at t-3 which is nearly the same during the last three years before failure. This size is significantly smaller than the average board size in European companies (11.8) as of 2009 (Heidrick and Struggles, 2009). The smaller board size could be due to New Zealand's small market and body of corporate directors. However, it is also smaller than New Zealand publicly listed companies which consist of an average of six members (Fauzi and Locke, 2012). According to Tables 5.1, the minimum (Min) and maximum (Max) number of members are two and nine respectively. This is smaller than the results of the top 50 Australia and New Zealand listed companies; 86% of them have between six and 11 board members (KORN/FERRY International in Association with Egan Associates, 2007). It is consistent, however, with the UK Companies Act (2006) which recommendations that a private company should have a minimum of one director and a public company must have a minimum of two.

Table 5-1 shows that the average director turnover (DIRCHANGE) is 42% to 47%, which is nearly the same for all three years before failure. However, the maximum number of directors appointed (DIRAPPOINT) and resigned (DIRRESIG) is higher at t-3 (7 and 6 respectively), compared to 4 members at t-2 and t-1. Fama (1980) notes that self-interested directors prefer to resign and leave a company when it is struggling before their reputation is compromised. Therefore, the number of changes within the board of directors teams increases when the company is at risk of failure (Hubbard and Kosnik, 1997).

As per Table 5.1, the mean values of related party transaction to total asset (RELAT_TA) are steady during the three years before failure. However, the mean value of related party transaction to total loan (RELAT_GLOAN) increases from 0.149 at t-3 to 0.190 at t-2 and then reduces to 0.169 at t-1. Although it reduces at t-1, it is still higher than t-3. It thus confirms the view that increasing levels of related party lending occur prior to failure. The results are also supported by Reserve Bank findings (2013) that New Zealand finance companies conducted a high level of related party lending. However, it is still smaller than related party lending by 17 Mexican banks, which in 1995 lent 20% to related parties (La Porta et al., 2003).

The next variable recruited is the independent external auditors (BIGN). A dummy variable “one” was assigned to companies that were audited by one of the Big 4 (Price Waterhouse Coopers, Deloitte, Ernst and Young and KPMG), otherwise “zero”. As shown in Table 5-1, the mean value of the auditor is nearly 0.58 for all of the three years before failure, indicating that about 58% of the sample companies used a Big 4 auditor. However, in their study of 31 New Zealand finance companies, Douglas et al., (2014) reported a much lower figure (35.5%). In addition, the mean value of audit modification (MODIFIED) reveals a sudden growth from 0.014 at t-3 and t-2 to 0.157 at t-1, an increase of 50%. The finding is consistent with Douglas et al., (2014) who explained that 17.70% of sampled companies received modified audit report in the year prior to failure. This result is very small in comparison to the United States firms. Carson et al., (2013) undertook a study on 396 bankrupt firms from 2000 to 2010 and concluded that 60.10% of bankruptcies were followed by going-concern uncertainties in their final reports before failure. It is relatively consistent with distressed Chinese companies; 18.1% companies received a prior-year modified report, in a sample of 5,131 companies throughout 2001 to 2010 (Mo, Rui, and Wu, 2015).

The audit lag (AUDITLAG) has a maximum value of 270 days at t-2, rather than the maximum 194 days at t-3 and 232 at t-1. It has a mean value of 114 days in t-2 and 105 in t-1. These findings are higher than Douglas et al.'s (2014). They found a maximum lag of 175 days and a mean value of 95.5 days. However, it is smaller than stressed U.K. companies, which had a mean value of 129.5 days a year, prior to failure, in a sample of 58 companies in 2003 (Basioudis, Papakonstantinou, and Geiger, 2008). It is higher than the United States financially distressed firms. Geiger et al.'s (2005) study of 226 companies over the period of 2000 to 2003 found a mean value of audit lag of 83.3 days in 2001 and 75.3 in 2003.

The results included in Table 5-1 indicate that the mean value of audit remuneration natural log (LG.AUDREM) increases from 4.06 and 4.05 at t-3 and t-2, respectively, to 4.27 at t-1. The maximum value also increased by 0.34 (from 5.37 in t-2 to 5.71 in t-1). In the other word, the maximum audit remuneration increases from 234,000 in t-2 to 511,000 in t-1. The findings are relatively similar with the mean value of 5 for 58 U.K. stressed companies (Basioudis et al., 2008). Li's (2009) study of 1681 distressed companies during pre-SOX (2001) and 1780 distressed companies during post-SOX (2003) found the increasing mean value of audit log fees; 5.20 in 2001 and 7.50 in 2003.

The mean value shows 95% (t-3 and t-2) and 97% (t-1) of New Zealand finance companies delegate supervision to one of the three known trustee companies (TRUSTEE). It is higher than the mean value of 86% noted by Douglas et al. (2014). However, their sample size is smaller than this study's sample size. Additionally, the trust deed amendment (AMENDED) increases from 0.071 at t-2 to 0.257 at t-1. This is similar to Wilson et al.'s (2013) finding that although trustees were aware of breaches in the terms and conditions of the trust deeds, they agreed to amend the definitions. In short, there are typically more amendments made to trust deeds closer to the time of failure.

The age of finance companies (AGE) ranges from one to 84 years. The result shows that the mean value for age is 14.64 years at t-1. This is comparable with Douglas et al. 's (2014) finding of 16.22 noted in a sample of 31 New Zealand finance companies.

The last Agency-related variable is media (MEDIA). The maximum value of media has a significant increase from 10 at t-3 and 6 at t-2 to 52 at t-1. The mean value also rose from 0.543 at t-2 to 3.671 at t-1. The finding is supported by Dyck et al. (2010) whose study reported on fraud cases among the United States companies between 1996 and 2004. This study shows that media reported 10 of the 11 fraud cases in New Zealand.

Table 5-1 shows that total equity to total asset (TE_TA), the first capital adequacy ratio, has a significant reduction in minimum value from -0.021 at t-3 to -307.52 at t-1, indicating the mean value for this variable also decreases from 0.201 at t-3 to -5.07 at t-1. It shows that total liability, which is outstanding loans to depositors, has a sudden increase and the company is in debt, resulting in a decrease in capital adequacy. Canbas et al. (2005) proved that a decrease in capital adequacy has a negative impact on the financial strength of the finance company and leads to a higher chance of default risk. Meanwhile, the minimum value for total asset to total liquidity (TA_TL) also drops from 0.979 at t-3 to -0.003 at t-1. In other word, the company's total liability is about 300 times more than its total assets in the year prior to failure. As the company does not maintain any capital for risk exposure, the risk of insolvency is definite in the case of any losses on the company's assets (Pilbeam, 2005).

It is supported by the maximum value of gross loan and advances to total asset (GLOAN_TA) of 0.992, which clearly explains that finance companies' main assets consist of funds lend to third parties which makes up nearly 100% of finance companies' asset base. Table 5-1 shows that the mean value of gross loans and advances to total assets is 0.718 for an average of three years, which is less than Kabir and Laswad's (2014) figure of 0.83. They obtained this figure by analysing New Zealand finance companies five years before failure.

Table 5-1 Descriptive Analysis

	T = 1						T = 2						T = 3					
	Min	Max	Mean	SD	Skewness	Kurtosis	Min	Max	Mean	SD	Skewness	Kurtosis	Min	Max	Mean	SD	Skewness	Kurtosis
NUMDIR	2.0	9.0	4.242	1.748	.822	.153	2.0	9.0	4.357	1.719	.549	-.568	2.0	9.0	4.400	1.564	.425	-.256
DIRCHANGE	0	1.0	.471	.502	.117	-2.046	0	1.0	.457	.501	.176	-2.028	0	1.0	.428	.498	.295	-1.970
DIRAPPOINT	0	4.0	.600	.969	1.578	1.776	0	3.0	.585	.859	1.206	.268	0	7.0	.657	1.088	3.226	15.843
DIRRESIG	0	4.0	.685	1.056	1.350	.715	0	4.0	.571	.956	1.784	2.595	0	6.0	.414	.924	3.826	19.370
RELAT-TA	0	0.989	.109	.196	2.402	6.153	0	.996	.115	.221	2.524	6.418	0	.993	.109	.243	2.887	7.574
RELAT-GLAON	0	1.0	.169	.299	1.967	2.639	0	1.0	.190	.329	1.745	1.617	0	1.0	.149	.296	2.202	3.482
BIGN	0	1.0	.585	.496	-.356	-1.929	0	1.0	.585	.496	-.356	-1.929	0	1.0	.571	.498	-.295	-1.970
MODIFIED	0	1.0	.157	.366	1.926	1.758	0	1.0	.0142	.119	8.367	70.0	0	1.0	.014	.119	8.367	70.000
AUDITLAG	6.0	232.0	105.20	46.45	.587	.295	6.0	270.0	113.95	61.296	.994	.565	1.0	249.0	94.757	45.800	0.795	1.100
LG.AUDREM	0	5.71	4.277	1.402	-2.423	5.169	0	5.37	4.053	1.533	-2.088	3.122	0	5.43	4.062	1.320	-2.508	5.440
TRUSTEE	0	3.0	.971	.9626	.460	-1.021	0	3.0	.957	.954	.499	-.940	0	3.0	.957	.954	.499	-.940
AMENDED	0	1.0	.257	.440	1.136	-.732	0	1.0	.071	.259	3.402	9.851	0	1.0	.100	.302	2.725	5.587
AGE	3	84	14.64	14.50	3.226	12.559	2	83	13.64	14.506	3.226	12.559	1	82	12.63	14.511	3.226	12.555
MEDIA	0	52.0	3.671	9.307	3.601	13.625	0	6.0	.543	1.247	2.782	7.665	0	10.00	0.414	1.302	6.113	43.633
TE-TA	-307.5	0.998	-5.07	37.13	-8.078	66.432	-.096	.998	.206	.233	2.093	4.311	-.021	.998	.201	.242	2.356	5.082
TA-TL	-.003	400.79	13.644	61.66	5.169	27.314	.912	434.846	15.116	68.214	5.110	26.410	.979	407.33	16.380	69.036	4.796	22.666
GLOAN-TA	0	0.992	.694	.301	-1.098	.003	0	0.997	.739	.269	-1.451	1.329	0	.995	.716	.292	-1.361	.757
LG. TL-TE	-2.52	3.86	.475	1.074	-.725	3.233	-2.70	4.02	.632	1.112	-.723	4.354	-3.45	3.89	.539	1.147	-1.419	3.879
IMPAIR-TA	0	0.854	.0451	.131	4.505	22.751	.001	.253	.0119	.034	5.582	36.731	0	.086	.005	.0147	3.752	15.347
DOUBT-GLOAN	-.006	0.850	.033	.120	5.738	34.842	-.015	.121	.009	.0189	3.617	17.669	-.001	.039	.006	.010	1.842	2.757
OE-OR	.106	276.73	7.258	34.00	7.684	61.268	.174	39.440	1.452	4.659	8.205	67.843	0	59.0	1.990	7.139	7.841	63.246
OE-TA	.011	67.521	2.640	9.720	5.691	34.196	-.011	40.214	1.169	4.892	7.712	62.025	0	12.355	.541	1.615	6.266	44.116
NPAT-TE	-2.890	10.850	.446	1.781	3.995	20.827	-8.025	4.0	.109	1.207	-3.923	31.549	-2.107	1.685	.221	.482	-.643	9.197
NPAT-TA	-309.356	.644	-6.438	39.25	-7.151	53.775	-.191	1.493	.050	.198	6.141	42.417	-.055	.482	.034	.077	4.615	23.900
NETINT-TA	-11.199	21.414	.214	2.910	4.863	45.089	-.116	3.391	.106	.402	8.068	66.629	-.098	12.355	.223	1.471	8.349	69.800
CA-TA	.036	1.0	.648	.246	-.568	-.053	.026	1.0	.642	.255	-.589	.046	0.043	1.0	.657	.306	-.433	-1.047
OCF-TA	-42.974	6.576	-.515	5.223	-7.973	65.926	-.402	2.108	.043	.268	6.724	52.555	-.574	.993	.040	.159	2.671	21.279
LG.TA	4.76	9.37	7.757	.845	-1.043	2.135	6.02	9.31	7.846	.679	-.137	-.256	5.89	9.44	7.760	.750	-.254	-.349

In addition, the maximum value of impairment of assets to total assets (IMPAIR_TA) and doubtful debt to gross loans and advances (DOUBT_GLOAN) has a substantial increase from 0.086 and 0.039 at t-3 to 0.253 and 0.121 at t-2 and 0.854 and 0.850 at t-1, respectively. As shown in Table 5-1, the mean value of impairment of assets to total asset is 4.51 at t-1, and doubtful debts to gross loans and advances is 3.35 at t-1. It is lower than Kenyan banks. Ongore and Kusa (2013) studied 35 commercial banks from 2001 to 2010 and calculated 15.52 as the mean value of asset quality. The rise in impairment of assets and doubtful debts indicates poor asset loan quality and a heightened risk of insolvency.

The range of operating expenses to operating revenue (OE_OR) is presented in Table 5-1. It ranges from zero to 59 at t-3, 0.174 to 39.44 at t-2 and 0.106 to 276.73 at t-1, indicating mean values of 1.99, 1.45 and 7.26 for the three years prior to failure, respectively. Although it has a small decrease of 20 at t-2, rather than t-3, it rises to 276.73 at t-1. Whereas, the trend of maximum value for operating expenses to total assets (OE_TA) has a gradual increase from 12.35 at t-3 to 40.21 at t-2 and then to 67.52 at t-1. As these two ratios are representative of management quality, the trend demonstrates a backward efficiency among distressed finance companies.

Net profit to total equity (NPAT_TE) is in the range of -2.107 to 1.685 at t-3 and expands to -2.890 to 10.850 at t-1, indicating mean values of 0.22 and 0.45 at t-3 and t-1, respectively. Meanwhile, the range of net profit to total asset (NPAT_TA) is -0.055 to 0.482 at t-3 and enlarges to -309.35 and 0.644 at t-1 with mean values of 0.034 and -6.44. In addition, net interest income to total assets (NETINT_TA) follows the same trend and expands from -0.098 and 12.35 at t-3 to -11.199 and 21.414 at t-1. These three ratios evaluate the quality of earnings and show management efficiency in generating income from the company’s resources (Khrawish, 2011). The trend of minimum figures indicates that distressed financial companies incur substantial losses closer to the year of failure. However, interpreting net profit to total equity needs more detail to be precise. Increasing maximum value does not necessarily indicate management efficiency or reflect the good position of a company. A company can incur huge losses without maintaining any assets; therefore, as a numerator, a loss figure is negative while equity is a denominator. Hence, the total ratio is a positive figure. This can be confusing if it is not interpreted correctly. Therefore, an increase in net profits to total equity from 4 at t-2 to 10.850 at t-1 while minimum value reduces from -8.025 at t-2 to -2.890 at t-1 is not real. However, the average mean value of net profit to total equity and net profit to total assets is 24.00 and -21.17 respectively. These figures differ significantly from previous studies, particularly Ongore and Kusa’s (2013) work on 35 Kenya commercial banks. They found mean values of 14.80 and 1.95 (Ongore and Kusa, 2013).

The current asset to total asset (CA_TA) ratio, with a minimum value of 0.043 at t-3, 0.026 at t-2 and 0.036 at t-1 and a maximum value of one for each of the three years does not show any notable trend in the three years before failure. However, in general, the minimum values of all three years are very small and do not show sufficient liquidity in case of company losses. Net operating cash flow to total asset (OCF_TA) is another proxy for liquidity risk. This ratio ranges from -0.574 and 0.993 at t-3 and -42.974 and 6.576 at t-1, indicating mean values of 0.041 and -0.516 at t-3 and t-1, respectively. The dramatic increase of -0.574 to -42.974 indicates inefficiency in managing operating activities, as operating expenses increase significantly, without any operating revenue.

Asset size (LG.TA) which refers to company size, is in the range of $57,483.00 to 2,326,243,000.00 at t-1. This range is between 1,038,978.00 and 2,048,568,000.00 at t-2. Minimum asset size shows a substantial reduction more than 981,000.00 from t-2 to t-1, which with knowledge of none of the company had a plan of downsizing; it explains the critical condition of the company. The loss of assets can be easily explained by high levels of impairment assets, doubtful debts and high operating expenses which are largely the results of inefficient management decisions. However, this study uses the natural log of asset size.

5.5 Univariate Analysis

This study firstly follows (Beaver, 1966) and uses univariate analysis to determine whether there are significant differences between key financial ratios and non-financial variables of failed and non-failed finance companies. The main tests compare whether there are differences between failed and non-failed companies in event time, where t is the year of failure (the non-failed company assumes the same t as the matched failed company). The objectives of this study include determining whether the proposed variables, analysed alone, might have an impact on financial institution failures before they are used in the model. As discussed earlier, financial variables are based on the CAMELS ratios and non-financial information based on Agency-related variables.

The univariate tests used here are the t-test for the parametric variables and the Mann-Whitney U test for non-parametric variables. The variables are parametric (normally distributed) if the skewness in the descriptive analysis is in the range of -2 to +2 and the kurtosis is in the range of -4 to +4, otherwise it is non-parametric. Additionally, the mean values are shown if the distribution is normal, and the median in the condition of non-normal distribution of data. Table 5.2 presents the results of the univariate tests. This test was run for all three time periods (t-3, t-2 and t-1) to provide more detail to ensure a better understanding.

As can be seen from the results in Table 5.2, the median value of total equity to total assets (TE-TA) and total assets to total liability (TA-TL) in the failed companies are lower than healthy companies for the three years before failure. This difference is highly significant in the year prior to failure. Furthermore, the total liquidity to total equity (TL-TE) is higher in failed companies than non-failed ones. It shows high proportions of liability, which in finance companies means deposits are higher than the company's equity. It is significantly high at t-2 (0.916), which is three times more than healthy companies (0.348) in the same year, whereas the median value of total assets to total liability is 1.125 and 1.192 for failed and non-failed companies, respectively. This suggests that the failed companies retain lower levels of capital than non-failed companies.

The results do not show any remarkable difference in asset quality between failed and non-failed companies. However, the median value of impairment of assets to total assets (IMPAIR-TA) is slightly higher among non-failed companies, for each of the three years. The difference is significant between two groups at t-3 (significant at the 1% level). For finance companies, assets are loans made, while impairment of assets refers to written-off loans. The higher impairment of assets is, the lower the quality of assets is. As Grier (2007) notes that poor asset quality is one of the main reasons most banks fail.

The median value of operating expenses to total assets (OE-TA) is significantly different at t-3 and t-2 among these two groups of companies (Table 5-2). However, it is interesting to note that the ratio is higher for non-failed companies in comparison with failed companies. In this case, by checking the net profit after tax to total equity (NPAT-TE) for t-3 and t-2, it is obvious that even if operating expenses are higher in healthy companies, the net profit to total equity is also higher, and companies could generate more profit than failed companies. In addition, operating expenses to operating revenue (OE-OR) is higher in failed companies than in healthy companies in the last two years before failure, indicating that failed companies have incurred more expenses and have generated less revenue compare to non-failed companies. Failed companies have significantly higher (NPAT-TE) than healthy companies in last year before failure. By looking at mean values of (TL-TE) as explained earlier, it is clear that failed companies have a very high proportion of liability as opposed to equity. On average, the mean value of (TL-TE) is twice for failed companies compared to non-failed companies. Management quality ratios presented in Table 5.2 show that the failed companies perform well. However, when this is viewed in conjunction with capital adequacy ratios, true performance is revealed.

The ratio of net profit after tax, before abnormal to total assets (NPAT-TA) is higher in non-failed companies at t-2 and substantially higher at t-1 before failure. Additionally, net interest income to total assets (NETINT-TA) is also higher among healthy companies during each of the three years separately, but it is only significant at t-3. These results show the better quality of earning among healthy companies.

The liquidity ratio results included in Table 5-2 are similar between the two groups. However, company size is significantly different between two groups a year prior to failure. This suggests that failed companies have smaller asset size compared to healthy companies. This result is in line with the concept of 'too big to fail.'

Overall, the results support the first objective and suggest that investors could have been able to infer from published financial information that finance companies were likely to fail up to three years earlier. However, as it is not clear that all of the ratios of finance companies suggest a higher risk, it is better to consider all of the ratios collectively.

The board composition variable results are similar at t-2 and t-1 for both groups. However, the board of director changes (DIRCHG), director appointed (DIRAPNT) and director resigned (DIRRSG) differ in failed and non-failed companies at t-3 (significant at the 1% level).

As shown in Table 5-2, among the Agency-related variables, the mean and median values of related party transaction to total assets (RELAT-TA) and related party transaction to total loans and advances (RELAT-GLOAN) are higher in failed companies up to three years before failure. For instance, the mean values of (RELAT-TA) and (RELAT-GLOAN) are 0.042 and 0.196 for failed companies relative to 0.003 and 0.143 for healthy ones at t-1, respectively.

The audit big (BIGN) variable is significant during the three years, which reveals that non-failed companies have chosen Big 4 as their auditor more than failed companies. Meanwhile, the failed companies received more audit modification reports (MODIFIED) than healthy companies a year prior to failure. However, only one finance company received qualified reports, and 17 companies received unqualified reports with 'fundamental uncertainties' or 'emphasis of matter' paragraphs in their audit report. The audit remuneration (AUDREM) and the number of days between the end of the financial year and the auditor sign-off date are similar for both failed and non-failed groups.

The test demonstrates the mean value of having one of the three trusts (X, Y and Z as explained in the Chapter Three) as the company trustee is higher among failed companies than non-failed companies at t-1. As no changes in trustee company has been observed in the sample test, the significant differences in trusteeship remain at t-2 and t-3. Hence, trusteeship can play an important role in trustee characteristics. In addition, failed companies had more changes in their trust deeds a year prior to failure than non-failed companies. The result is in line with Wilson et al. (2013) who claim that even though the trustee was aware of breaches in terms and conditions, they agreed to amend definitions in the trust deed to match the company's condition. Consequently, failed finance companies have different trustee characteristics in relation to healthy companies.

Differences in firm maturity (AGE), or the years from inception to data collection, are obvious among failed and healthy groups. As indicated in the literature, the risk of failure is higher among young companies. The median value of healthy companies is nearly twice that of failed companies. This finding is similar to Douglas et al.'s (2014) who concluded that healthy companies are more mature than failed companies. As Caudill et al. (2009) and Kyereboah-Coleman and Osei (2008) note, aged companies monitor their spending efficiently and concentrate on increasing profitability and financial sustainability (Nurmakhanova et al., 2015).

As the last Agency-related variable, media has similar results for failed and non-failed companies. The number of published reports about the finance companies, regardless of positive or negative news, is the same for both failed and non-failed companies. The result indicates that media in New Zealand have not played an effective monitoring role in relation to local finance companies.

In summary, the univariate statistics based on the t-test and the Mann Whitney U test provide preliminary results which suggest that both financial and non-financial variables have discriminatory power among failed and non-failed companies.

Table 5-2 Univariate Table

CAMELS Variables	T = 1 Failed Mean	Non-failed Mean	t-stat	z-score	T = 2 Failed Mean	Non-failed Mean	t-stat	z-score	T = 3 Failed Mean	Non-failed Mean	t-stat	z-score	T = Average Failed Mean	Non-failed Mean	t-stat	z-score
TE-TA	0.095	0.178		-3.248***	0.111	0.169		-1.709*	0.117	0.154		-0.687	0.109	0.163		-2.848***
TA-TL	1.105	1.217		-3.248***	1.125	1.192		-1.392	1.132	1.182		-0.734	1.126	1.196		-2.132**
GLOAN-TA	0.645	0.743	-1.367		0.722	0.757	-0.537		0.725	0.707	0.254		0.700	0.736	-0.573	
TL-TE	0.616	0.334	1.101		0.916	0.348	2.197**		0.715	0.365	1.283		0.805	0.371	1.668	
IMPAIR-TA	0.004	0.003		-0.378	0.000	0.002		-1.109	0.000	0.001		-1.862*	0.002	0.003		-0.233
DOUBT-GLOAN	0.004	0.002		-0.778	0.000	0.004		-0.929	0.004	0.008	-1.648		0.006	0.003		-0.233
OE-OR	0.913	0.814		-0.190	0.879	0.833		-0.540	0.758	0.842		-1.061	0.867	0.751		-2.620***
OE-TA	0.164	0.242		-1.626	0.123	0.270		-2.196**	0.101	0.273		-3.123***	0.141	0.158		-0.816
NPAT-TE	0.202	0.142		-0.769	0.101	0.116		-0.253	0.187	0.256	-0.602		0.108	0.102	1.992**	
NPAT-TA	-0.006	0.015		-2.778***	0.012	0.027		-2.226**	0.018	0.018		-1.010	0.001	0.023		-3.013***
NETINT-TA	0.058	0.070		-0.852	0.048	0.070		-1.580	0.034	0.068		-2.020**	0.052	0.067		-0.899
CA-TA	0.684	0.610	1.247		0.693	0.590	1.710*		0.708	0.626	1.117		0.686	0.606	1.431	
OCF-TA	0.012	0.022		-1.183	0.017	0.011		-0.476	0.028	0.016		-0.383	0.020	0.067		-1.687*
LG-TA	7.542	7.973	-2.185**		7.736	7.956	-1.366		7.657	7.863	-1.151		7.712	7.943	-1.362	-0.265
Agency variables																
BCNUMDIR	4.228	4.257	-0.068		4.228	4.485	-0.623		4.314	4.486	-0.456		4.257	4.409	-0.404	
DIRCHANGE	0.486	0.457	0.236		0.400	0.514	-0.952		0.314	0.543	-1.957*		0.400	0.505	-1.181	
DIRAPPOINT	0.685	0.514	0.738		0.514	0.657	-0.693		0.000	1.000		-1.782*	0.600	0.628	-0.173	
DIRRESIG	0.657	0.714	-0.225		0.571	0.571	0.000		0.000	0.000		-1.902*	0.514	0.600	-0.546	
RELAT-TA	0.042	0.003		-1.397	0.017	0.003		-1.505	0.025	0.000		-1.260	0.032	0.002		-1.984**
RELAT-GLAON	0.196	0.143	0.731		0.243	0.138	1.336		0.036	0.000		-1.384	0.073	0.005		-2.002**
BIGN	0.400	0.771	-3.357***		0.400	0.771	-3.357***		0.371	0.771	-3.643***		0.390	0.771	-3.478***	
MODIFIED	0.286	0.028	3.114***		0.000	0.000		-1.000	0.000	0.000		-1.000	0.000	0.000		-3.280***
AUDITLAG	113.686	96.714	1.543		114.628	113.286	0.091		90.000	99.514	-0.867		106.095	103.171	0.306	
LG.AUDREM	4.544	4.778		-0.118	4.492	4.520		-0.370	4.312	4.505		-1.175	4.527	4.622		-0.018
TRUSTEE	1.343	0.600	3.478***		1.314	0.600	3.355***		1.314	0.600	3.355***		1.324	0.600	3.403***	
AMENDED	0.371	0.143	2.234**		0.000	0.000		-0.461	0.000	0.000		-0.396	0.190	0.095	1.808*	
AGE	7.000	14.00		-3.499***	6.000	13.000		-3.499***	5.000	12.000		-3.528***	6.000	13.000		-3.499***
Media	0.000	0.000		-0.744	0.000	0.000		-0.454	0.000	0.000		-0.634	0.000	0.000		-0.607

5.6 Multicollinearity

Table 5-3 to 5-6 present pairwise correlation matrixes of the explanatory variables through Spearman's rank correlations; this appropriate for nonparametric variables. Knowledge of correlations is useful for model development because a high correlation between two important variables could be the reason why only one of the variables should be included in the model. As the models are tested in years t-1, t-2, t-3 and the combined three years, the correlations are tested separately for each time. In the case of highly correlated variables, both of them are tested separately in the model, and the variable with a better result is used in the models while the other one is excluded.

The existence of a strong correlation between independent variables is tested using the Variance Inflation Factor (VIF). Correlation coefficients greater than 0.85 between two variables will result in multicollinearity problems. This is when both of the variables are entered into the regression (Gujarati and Porter, 2011).

At t-1, the ratio of related party transaction to total assets is correlated with the ratio of the related party transactions to gross loans and advances at 0.979**. Table 5-3 shows that total assets to total liability and total equity to total assets are highly correlated at 1.00**and net operating cash flow to total assets is correlated with operating expenses to operating revenue at -0.864**. Therefore, the ratios of related party transactions to gross loans and advances, total equity to total assets and operating expenses to operating revenue are eliminated from model development at t-1.

Related party transactions to total assets is again correlated with related party transactions to gross loans and advances at 0.959** at t-2. Moreover, total assets to total liability and total equity to total assets are highly correlated at 0.955**. GDP and OCR variables are correlated at 0.885** and Inflation and HPI at 0.863** (Table 5-4). Hence, related party transactions to gross loans and advances, total equity to total assets and OCR and HPI were removed from the t-2 model.

The related party transactions to gross loans and advances, total equity to total assets ratios and OCR were eliminated at t-3 due to high correlation with related party transactions to total assets, total assets to total liability and GDP at 0.981**, 0.998** and 0.888**, respectively (Table 5-5).

Table 5-6 shows that the ratio of related party transactions to total assets is correlated at 0.972** with related party transactions to gross loans and advances in combined data for three years before failure. Likewise, total assets to total liability and total equity to total assets are highly correlated at 0.985**.

Most of the independent variables are less than 0.5 which is considered to be a low correlation between independent variables. Therefore, there is less concern about multicollinearity.

Table 5-3 Correlation Matrix T = 1

	NUMDIR	DIRCHANGE	DIRAPPOINT	DIRRESIG	RELAT-TA	PELAT-GLAON	BIGN	MODIFIED	AUDITLAG	AUDREM	TRUSTEE	AMENDED	LnAGE	MEDIA	TE_TA	TA-TL
NUMDIR	1															
DIRCHANGE	0.226	1														
DIRAPPOINT	.296*	.698**	1													
DIRRESIG	0.016	.767**	.460**	1												
RELAT-TA	.244*	-0.011	0.073	0.016	1											
PELAT-GLAON	0.215	-0.014	0.072	0.027	**.979****	1										
BIGN	.363**	0.155	0.129	0.156	-0.036	-0.001	1									
MODIFIED	-0.088	-0.015	0.046	0.139	0.177	0.229	-0.115	1								
AUDITLAG	0.019	.284*	.369**	0.213	0.029	0.036	-0.002	.240*	1							
AUDREM	.332**	.329**	0.094	.253*	0.135	0.11	0.16	0.089	0.196	1						
TRUSTEE	0.094	-0.013	-0.02	-0.134	0.221	0.17	-.299*	-0.036	-0.149	0.115	1					
AMENDED	-0.14	-0.032	-0.017	0.02	0.142	0.138	-0.102	0.105	0.105	0.15	0.182	1				
LnAGE	.263*	-0.003	0.01	-0.024	-0.124	-0.178	.257*	-0.215	-0.202	.348**	-0.121	-0.153	1			
MEDIA	0.07	.294*	0.075	0.189	-0.018	0.007	0.101	.294*	0.186	.346**	0.159	0.024	-0.037	1		
TE-TA	-0.135	-0.182	-0.23	-0.11	-0.216	-.237*	0.028	-0.228	-.299*	-0.101	-.282*	-0.002	0.109	-.375**	1	
TA-TL	-0.133	-0.178	-0.226	-0.11	-0.218	-.238*	0.029	-0.232	-.300*	-0.101	-.281*	-0.005	0.108	-.376**	**1.000****	1
GLOAN-TA	0.05	-0.193	-0.113	-0.158	0.097	0.025	0.118	-.252*	-.331**	-0.013	0.09	-0.217	0.195	0.002	0.044	0.047
TL-TE	0.08	0.079	.246*	0.162	0.197	0.233	-0.047	0.186	0.073	0.156	-0.092	0.163	0.01	-0.18	-.341**	-.341**
IMPAIR-TA	0.058	0.166	-0.058	0.07	-0.004	-0.027	0.022	0.066	0.074	.551**	0.066	0.127	0.139	.331**	-0.088	-0.088
DOUBT-GLOAN	0.012	0.077	-0.1	0.105	-0.01	-0.025	-0.113	0.103	0.012	.350**	0.132	0.232	0.039	0.084	0.006	0.008
OE-OR	0.174	0.129	0.219	-0.022	0.04	0.044	.270*	-0.011	0.238	0.127	-0.162	-.239*	0.119	-0.107	-.247*	-.245*
OE-TA	0.097	0.201	0.193	0.14	-0.177	-0.182	.292*	-0.032	.298*	0.036	-0.163	-0.182	0.118	0.116	-0.076	-0.074
NPAT-TE	0.021	0.14	0.147	0.059	0.076	0.086	-0.037	-0.143	0.09	-0.194	.324**	-0.162	-0.124	0.194	-.362**	-.361**
NPAT-TA	-0.167	-0.178	-0.021	-0.081	-0.148	-0.17	-0.085	-.333**	-0.229	-.327**	-0.106	-0.011	0.12	-.466**	.521**	.522**
NETINT-TA	-0.181	-0.111	-0.082	-0.098	-0.13	-0.131	0.029	-0.176	-0.025	-0.047	0.055	0.042	0.079	0.077	0.132	0.13
CA-TA	-0.037	-0.184	-0.14	-0.094	0.135	0.103	-.245*	-0.039	-0.151	-0.204	.287*	0.059	-0.176	0.009	-0.103	-0.105
OCF-TA	-.268*	-0.076	-0.206	0.067	-0.185	-0.2	-.275*	-0.057	-0.216	-0.122	0.122	0.156	0.018	0.061	.272*	.272*
TA	.389**	0.132	0.138	0.108	0.132	0.117	.355**	-0.086	-0.072	.480**	-0.177	0.04	.440**	0.092	-0.158	-0.158
GDP	-0.117	-0.195	-0.131	-0.039	-.242*	-.250*	-.267*	0.042	-0.105	-0.011	0.014	-0.17	-0.039	-0.091	0.159	0.161
INFLAT	-0.148	-.391**	-.283*	-.365**	0.085	0.051	-0.214	-0.018	-0.104	-.339**	0.055	0.107	-0.112	-.522**	.281*	.280*
OCR	-.293*	-.326**	-0.154	-.244*	-0.113	-0.145	-.416**	-0.095	-0.142	-.322**	0.119	0.039	-0.162	-.494**	.250*	.252*
HPI	-0.1	-0.103	0.084	-0.106	0.052	0.031	-0.171	-.308**	-0.109	-0.151	0.078	0.204	-0.083	-.382**	0	0.005

	GLOAN-TA	LG.TL-TE	IMPAIR-TA	DOUBT-GLOAN	OE-OR	OE-TA	NPAT-TE	NPAT-TA	NETINT-TA	CA-TA	OCF-TA	TA	GDP	INFLAT	OCR	HPI
GLOAN-TA	1															
TL-TE	-0.17	1														
IMPAIR-TA	.261*	-0.079	1													
DOUBT-GLOAN	0.031	0.037	.473**	1												
OE-OR	-0.077	0.205	0.062	-0.054	1											
OE-TA	-0.075	-0.07	0.046	-0.17	.542**	1										
NPAT-TE	0.084	-0.129	-0.212	-0.191	-0.092	0.036	1									
NPAT-TA	0.128	0.064	-.358**	-0.151	-0.203	-0.2	.275*	1								
NETINT-TA	.288*	-.387**	.271*	-0.019	-0.021	.260*	0.123	0.11	1							
CA-TA	-0.037	-0.054	-.270*	-0.222	-.314**	-0.123	0.032	-0.077	-0.008	1						
OCF-TA	0.117	-0.206	0.002	0.117	**-.864****	-.275*	0.121	.262*	0.147	0.102	1					
TA	0.206	.263*	0.183	0.146	0.108	-.272*	-0.157	-0.057	-0.204	-0.238	-0.109	1				
GDP	0.028	-0.03	-0.202	-0.139	-0.18	-0.009	0.032	0.121	0.038	0.236	0.138	-0.231	1			
INFLAT	-0.119	0.083	-.326**	-0.219	-0.185	-0.131	-0.043	.271*	-0.163	0.145	0.14	-.336**	0.145	1		
OCR	-0.08	0.01	-.369**	-0.102	-0.182	-0.159	0.069	.404**	-0.01	0.232	0.169	-.306**	.580**	.625**	1	
HPI	0.116	0.082	-0.212	0.21	0.041	-.295*	0.13	.361**	-0.02	0.031	-0.065	0.162	0.054	-0.095	.386**	1

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Table 5-4 Correlation Matrix T = 2

	NUMDIR	DIRCHANGE	DIRAPPOINT	DIRRESIG	RELAT-TA	PELAT-GLAON	BIGN	MODIFIED	AUDITLAG	AUDREM	TRUSTEE	AMENDED	LnAGE	MEDIA	TE_TA	TA-TL	GLOAN-TA	LG.TL-TE	IMPAIR-TA	DOUBT-GLOAN	OE-OR	OE-TA	NPAT-TE	NPAT-TA	NETINT-TA	CA-TA	OCF-TA	TA	GDP	INFLAT	OCR	HPI
NUMDIR	1																															
DIRCHANGE	.257*	1																														
DIRAPPOINT	.376**	.767**	1																													
DIRRESIG	0.011	.719**	.491**	1																												
RELAT-TA	0.145	-0.051	-0.019	-0.213	1																											
PELAT-GLAON	0.145	-0.095	-0.048	-.238*	.959**	1																										
BIGN	.353**	.364**	.283*	.290*	-0.075	-0.079	1																									
MODIFIED	0.122	-0.11	-0.09	-0.085	0.114	0.089	-0.143	1																								
AUDITLAG	-0.112	0.035	-0.108	0.095	-0.027	-0.07	-0.034	0.17	1																							
AUDREM	.439**	.301*	0.219	.290*	-0.05	-0.129	0.209	0.054	0.229	1																						
TRUSTEE	0.038	-0.073	-0.115	-0.097	0.14	0.126	-.318**	0.022	-0.07	0.144	1																					
AMENDED	0.169	0.191	.312**	0.046	0.099	0.094	0.121	-0.033	0.133	0.147	0.067	1																				
LnAGE	.254*	0.083	0.146	-0.021	-0.142	-0.224	.257*	0.018	-0.034	.310**	-0.139	-0.019	1																			
MEDIA	.427**	0.22	0.203	0.082	0.154	0.117	.254*	.254*	-0.028	.447**	0.158	.291*	0.122	1																		
TE-TA	0.021	0.05	0.076	0.067	-0.215	-0.204	0.091	-0.206	-0.069	-0.172	-0.123	-0.075	0.052	-0.086	1																	
TA-TL	0.054	0.081	0.102	0.089	-0.178	-0.168	0.06	-0.206	-0.046	-0.123	-0.081	-0.065	0.021	-0.066	.955**	1																
GLOAN-TA	0.021	-0.153	-0.16	-.285*	0.093	-0.025	0.001	0.206	-0.112	-0.001	0.153	-0.194	0.051	0.051	-0.154	-0.129	1															
TL-TE	0.015	0.077	0.025	0.03	.270*	.268*	-0.113	-0.152	0.048	.270*	0.084	0.117	-0.105	-0.053	-.781**	-.744**	-0.035	1														
IMPAIR-TA	-0.007	0.074	-0.091	0.06	-0.028	-0.103	-0.007	0.211	.479**	.437**	-0.039	0.061	0.164	0.091	-0.109	-0.069	0.204	0.026	1													
DOUBT-GLOAN	0.021	-0.097	-0.038	-0.01	-0.068	-0.118	-0.088	0.15	0.203	0.233	0.081	0.09	0.087	0.009	-0.083	-0.049	0.003	0.043	.249*	1												
OE-OR	0.04	0.215	0.154	0.173	0.085	0.072	0.221	-0.164	.259*	.286*	0.031	.241*	-0.02	0.083	-0.193	-0.137	-0.16	0.232	0.235	0.067	1											
OE-TA	0.029	.263*	0.206	0.229	-0.218	-.260*	.329**	0.03	.311**	0.193	-0.151	0.135	0.169	0.052	-0.011	-0.052	0.07	-0.015	.271*	-0.016	.325**	1										
NPAT-TE	0.147	-0.23	-0.164	-.391**	0.095	0.138	0.001	0.188	-0.178	-0.098	0.001	-0.062	0.148	-0.005	-0.025	-0.082	0.071	0.12	-0.172	-0.128	-.359**	-0.068	1									
NPAT-TA	0.037	-0.123	-0.027	-.306*	-0.067	-0.033	0.05	-0.206	-0.233	-.354**	-0.02	-0.078	0.173	-0.091	.552**	.495**	0.008	-.459**	-.317**	-0.228	-.416**	-0.113	.590**	1								
NETINT-TA	-0.099	-0.034	-0.114	-0.129	-0.049	-0.094	0.12	0.063	0.147	0.039	-0.067	-0.012	0.076	-0.141	.240*	0.179	0.169	-.259*	.464**	0.124	0.09	0.214	-0.046	-0.016	1							
CA-TA	-0.072	-0.051	0.015	-0.04	0.027	-0.066	-.276*	0.085	-0.111	-0.084	.342**	0.132	-0.149	0.138	-0.075	-0.084	0.132	0.009	-0.152	-0.174	0.053	-0.147	-0.065	-0.035	-0.189	1						
OCF-TA	-0.09	-0.145	-0.113	-0.122	-0.195	-0.173	-.293*	0.188	-0.176	-0.191	0.078	-.282*	0.044	-0.104	0.12	0.058	0.12	-0.158	-0.232	0.095	-.825**	-.321**	.389**	.425**	-0.114	0.049	1					
TA	.489**	0.226	0.213	0.178	0.074	0.054	.335**	0.021	-0.101	.540**	-0.121	0.026	.342**	.408**	-.306*	-.259*	0.108	.246*	.252*	0.048	0.035	-0.047	-0.063	-0.233	-0.133	-0.227	-0.115	1				
GDP	0.208	0.015	0.005	0.012	-0.098	-0.053	0.171	0.062	0.09	0.105	-0.057	-0.009	0.083	0.175	0.165	0.213	-0.14	-0.132	-0.026	-0.083	.259*	.304*	-0.139	-0.144	-0.007	-0.027	-.255*	-0.058	1			
INFLAT	0.195	0.194	0.223	0.086	-0.097	-0.097	0.118	0.136	0.079	.340**	0.04	0.157	0.031	.355**	-0.102	-0.107	0.019	0.046	0.203	0.026	0.156	.254*	0.013	-0.163	0.095	-0.014	-0.226	.269*	0.081	1		
OCR	0.086	0.068	0.015	0.026	-0.21	-0.176	0.036	0.062	0.087	0.047	0.019	-0.014	0.016	0.125	0.168	0.192	-0.207	-0.138	-0.021	-0.05	.244*	.280*	-0.107	-0.105	0.059	-0.001	-0.208	-0.139	.885**	0.22	1	
HPI	-.283*	-0.139	-0.206	-0.105	0.177	0.182	-0.193	-0.136	-0.089	-.397**	0.058	-0.105	-0.121	-.292*	0.053	0.051	-0.045	0.062	-0.232	0.005	-0.187	-.282*	0.081	0.23	-0.143	0.016	.277*	-.270*	-.247*	-.863**	-.350**	1

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Table 5-6 Correlation Matrix three years

	NUMDIR	DIRCHANGE	DIRAPPOINT	DIRRESIG	RELAT-TA	RELAT-LAON	BIGN	MODIFIED	AUDITLAG	LG.AUDREM	TRUSTEE	AMENDED	LnAGE	MEDIA	TE-TA	TA-TL	GLOAN-TA	TL-TE
NUMDIR	1																	
DIRCHANGE	.262**	1																
DIRAPPOINT	.319**	.760**	1															
DIRRESIG	0.1	.712**	.483**	1														
RELAT-TA	0.135	0.011	0.069	-0.059	1													
RELAT-GLAON	0.11	0.002	0.067	-0.068	.972**	1												
BIGN	.355**	.345**	.301**	.297**	-0.041	-0.029	1											
MODIFIED	-0.036	-0.035	-0.015	0.064	0.132	.151*	-0.102	1										
AUDITLAG	-0.042	0.12	0.093	0.093	-0.049	-0.064	-0.024	.185**	1									
LG.AUDREM	.394**	.297**	.173*	.278**	0.061	0.013	.197**	0.091	.153*	1								
TRUSTEE	0.067	-0.131	-0.115	-0.134	.180**	.148*	-.322**	-0.009	-.166*	0.085	1							
AMENDED	0.003	0.039	0.067	-0.015	0.128	0.121	0.016	0.121	0.045	.149*	.176*	1						
LnAGE	.224**	0.087	0.118	0.101	-0.093	-.154*	.257**	-0.079	-0.082	.345**	-0.129	-0.072	1					
MEDIA	.165*	0.134	0.041	0.058	0.034	0.027	0.1	.262**	0.046	.320**	.156*	.177*	0.06	1				
TE-TA	-0.048	-0.053	-0.078	-0.034	-.167*	-.178**	0.013	-.187**	-.186**	-.150*	-.142*	-0.118	0.045	-.169*	1			
TA-TL	-0.04	-0.045	-0.072	-0.029	-.156*	-.167*	0.001	-.186**	-.179**	-0.132	-0.129	-0.115	0.032	-.163*	.985**	1		
GLOAN-TA	-0.016	-.164*	-.158*	-.166*	.144*	0.058	0.051	-0.083	-0.126	-0.038	0.101	-.161*	0.07	-0.014	-0.054	-0.045	1	
TL-TE	0.113	0.047	0.107	0.085	.215**	.211**	-0.082	0.071	0.132	.257**	0.028	.138*	-0.052	-0.104	-.603**	-.590**	0.001	1
IMPAIR-TA	0.002	0.13	-0.01	0.129	-0.002	-0.044	0.049	.152*	.236**	.482**	-0.037	0.064	.222**	.153*	-0.078	-0.063	.216**	0.006
DOUBT-GLOAN	-0.014	-0.049	-0.053	0.051	-0.075	-0.099	-0.07	0.113	0.128	.309**	0.062	0.12	0.116	0.044	-0.039	-0.025	0.029	0.07
OE-OR	0.037	.150*	.158*	0.021	0.033	0.042	.163*	0.007	.253**	.149*	-0.136	-0.073	0.041	-0.054	-.236**	-.219**	-0.118	0.135
OE-TA	-0.029	.201**	.166*	.171*	-.185**	-.209**	.243**	0.051	.367**	0.114	-.202**	-0.012	.211**	0.064	-0.081	-0.093	0	-0.036
NPAT-TE	0.063	-0.109	-0.077	-0.122	0.067	0.093	-0.011	-0.033	-0.045	-0.122	.192**	-0.045	0.027	0.095	-.201**	-.218**	0.08	0.018
NPAT-TA	-0.018	-.182**	-0.086	-.171*	-0.033	-0.038	-0.04	-.262**	-.199**	-.292**	0.006	-0.093	0.092	-.212**	.521**	.505**	0.089	-.206**
NETINT-TA	-.178**	-0.088	-0.123	-0.051	-0.055	-0.075	0.045	-0.012	0.081	-0.001	-0.064	-0.024	0.108	-0.03	.160*	.143*	.249**	-.274**
CA-TA	-0.049	-0.023	-0.006	-0.024	0.091	0.059	-.185**	-0.042	-.156*	-.141*	.227**	0.061	-.171*	0.031	-0.064	-0.064	0.046	-0.044
OCF-TA	-0.111	-0.102	-0.132	0.021	-0.102	-0.105	-.199**	0.007	-.181**	-0.095	.137*	0.034	0.041	0.035	.150*	0.133	0.099	-0.088
LG.TA	.455**	.212**	.185**	.187**	0.06	0.042	.349**	-0.063	-0.101	.527**	-0.133	0.06	.373**	.202**	-.246**	-.233**	0.112	.261**
GDP	.162*	.164*	0.115	.155*	-0.134	-0.114	0.068	0.03	0.013	.222**	-0.035	-0.004	0.078	0.063	0.079	0.093	-0.065	-0.057
INFLAT	-0.027	-0.103	-0.06	-.149*	-0.032	-0.035	-0.073	-0.077	0.055	-0.095	0.011	0.001	-0.041	-.150*	0.11	0.102	-0.059	0.041
OCR	0.023	0.056	0.067	0.009	-.163*	-.152*	-0.082	-0.126	-0.033	-0.034	0.033	-0.033	-0.042	-.236**	.173*	.175*	-0.123	-0.025
HPI	-.178**	-.159*	-0.079	-.149*	0.098	0.087	-.162*	-.198**	-.152*	-.268**	0.087	0.02	-.170*	-.286**	-0.008	-0.002	0.047	0.107

	IMPAIR-TA	DOUBT-GLOAN	OE-OR	OE-TA	NPAT-TE	NPAT-TA	NETINT-TA	CA-TA	OCF-TA	LG.TA	GDP	INFLAT	OCR	HPI
IMPAIR-TA	1													
DOUBT-GLOAN	.446**	1												
OE-OR	0.118	0.013	1											
OE-TA	.227**	0.012	.473**	1										
NPAT-TE	-.148*	-0.115	-.185**	-0.015	1									
NPAT-TA	-.275**	-.152*	-.377**	-.196**	.479**	1								
NETINT-TA	.401**	.153*	0.054	.284**	0.035	0.059	1							
CA-TA	-.210**	-.222**	-0.089	-0.115	-0.05	-0.076	-0.1	1						
OCF-TA	-0.049	0.128	-.817**	-.261**	.239**	.356**	0.059	0.079	1					
LG.TA	.201**	0.089	0.015	-.160*	-0.086	-.148*	-.168*	-.229**	-0.074	1				
GDP	0.018	-0.079	0.013	.151*	-0.019	-0.062	0.007	0.131	-0.051	0.066	1			
INFLAT	-0.13	-0.113	-0.042	0.044	-0.081	0.059	-0.055	0.124	-0.024	-0.095	-0.06	1		
OCR	-.157*	-0.091	-0.064	0.007	0.024	.166*	-0.043	.176*	0.023	-0.056	.709**	.326**	1	
HPI	-.207**	0.056	-0.11	-.284**	0.113	.286**	-0.097	-0.046	.150*	-0.085	-.198**	-.451**	-0.029	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

5.7 Logistic Regression Analysis

Binary logistic regression models are the first group of models employed to investigate the likelihood of failure among financial companies. As required by this model, institutions classified as failed were assigned a value of one or zero otherwise. The models were formed based on three different variable groups while using three different time intervention. The first model incorporates only CAMELS variables, whereas the second model uses Agency-related variables. CAMELS and Agency-related variables were integrated to form the third model. In addition to the above variables, four macroeconomic indicators of; Gross Domestic Product (GDP), Inflation, Official Cash Rate (OCR) and House Price Interest Rate (HPI) were included in all of the models.

Since the logistic estimates were obtained using maximum likelihood estimates, a log likelihood statistic was used to assess model fit. In addition, Nagelkerke R Square (also called "Psedu R^{2}") indicates the number of observations in the sample that an estimated equation classifies correctly. The Hosmer-Lemeshow goodness of fit is also another way to measure an overall fit and was used to test the null hypothesis that the model fits the data. The results are discussed in the following sections.

5.7.1 CAMELS Variables and Failure

Table 5-7 presents the result estimates for the first model. It only includes financial variables at one (t-1), two (t-2) and three (t-3) years prior to failure. The results show that TA-TL, TL-TE, OE-TA and TA are statistically significant from three years prior to failure, which suggest that they are efficient predictors of the probability of failure in finance companies. Moreover, three more regressors (IMPAIR-TA, NETINT-TA and OCT-TA) are statistically significant at 1% - 5% levels at t-2, or two years before companies fail. The IMPAIR-TA regressor retains its statistical significance at 10% at t-3. In addition, OE-OR, NPAT-TE and NPAT-TA are significant at t-3. The fact that most of the variables in Model 1 especially at t-2 and t-3 are significant suggests that the financial ratios possess a high degree of discriminatory power and prediction capability.

Furthermore, as shown in Table 5-7, the TA-TL coefficient is about 0.033 for three years. Although this ratio is statistically significant, the small coefficient amount makes the ratio economically insignificant. On the contrary, the TL-TE coefficient is between 2.75 to 3.97 for three years. The higher the ratio, the higher the probability of failure. High levels of liability as opposed to equity shows low capital adequacy. The results are consistent with the univariate test results that were discussed in the previous section.

Table 5-7 Model 1

Variable	MDL 1-1	MDL 1-2	MDL 1-3
TA-TL	0.036** (4.595)	0.030** (5.063)	0.033** (5.209)
GLOAN-TA	-0.096 (0.003)	1.534 (0.536)	-0.954 (0.182)
TL-TE	3.485** (5.849)	2.749** (5.105)	3.978** (6.274)
IMPAIR-TA	22.216 (1.203)	48.582** (4.334)	101.660* (2.958)
DOUT-GLOAN	19.342 (0.674)	40.333 (2.156)	-166.300 (2.010)
OE-OR		-0.149 (1.155)	4.359** (3.870)
OE-TA	-1.066* (3.373)	-3.645*** (7.529)	-40.985*** (8.870)
NPAT-TE	0.802 (0.600)	1.928 (1.609)	3.243* (3.444)
NPAT-TA	-5.335 (0.491)	16.953 (1.649)	-23.393** (4.975)
NETINT-TA	-3.947 (0.106)	-32.194** (4.436)	-1.577 (0.007)
CA-TA	0.925 (0.160)	-0.030 (0.000)	-1.303 (0.520)
OCF-TA	0.648 (0.020)	-40.858*** (6.871)	11.771 (1.387)
TA	-1.495** (4.129)	-1.370* (3.574)	-3.611*** (8.016)
GDP	0.019 (0.137)	-0.007 (0.033)	-0.043 (0.314)
INFLAT	1.356 (1.287)	-0.704 (1.010)	-3.732* (2.871)
OCR	-0.498 (1.247)		
HPI	0.116 (0.765)		-0.636 (1.892)
Cons	4.695 (0.211)	12.930 (2.697)	52.630** (4.004)
MDL chi-square	45.039***	44.969***	55.788***
-2 LL	49.170	50.671	38.421
H&L	5.767	4.159	5.373
$NagR^2$	0.646	0.639	0.747
Total class%	82.40	84.10	83.80

Number in parentheses is Wald Chi-square
*Significant at the 0.10 level
**Significant at the 0.05 level
***Significant at the 0.01 level

In addition, the high ratio of 48.52 for IMPAIR-TA in year two and a significantly high ratio of 101.66 for year three before failure demonstrate a high level of impairment assets relative to total assets. This shows the low quality of assets and the high probability of failure. The negative ratio sign of OE-TA, which represents a measure of the financial institution’s management competency, suggests that higher levels of operating expenses relative to total assets equal lower management performance. This ultimately indicates a higher probability of failing. Similarly, NPAT-TA and NETINT-TA signs reveal that the higher the earnings of the company, the lower the likelihood of failure. The OCF-TA also displays an anticipated negative sign. This indicates that the higher the proportion of net operating cash flow to total assets results in higher liquidity and hence a lower probability of failure. Meanwhile, total assets (which represents the size of the company), with a maximum estimated coefficient of -3.611 at t-3, suggests that size has a reverse impact on the likelihood of failure, meaning that failed companies have lower asset sizes.

The overall fit statistics (or log likelihood tests) are all significant. The Hosmer-Lemeshow test indicates that the model is a good enough fit and the model is a valid representation of the data. Models 1-1, 1-2 and 1-3 explain 64.6%, 63.9% and 74.7% of the variation in the data, respectively.

5.7.2 Agency-related Variables and Failure

The resulting estimates for the second model that incorporates only Agency-related variables at one (t-1), two (t-2) and three (t-3) years prior to failure are depicted in Table 5-8. The negative sign of BIGN, which represents audit quality, or whether choosing a Big 4 auditor has an impact on failure or not, suggests that finance companies who select any audit company except for a Big 4 one increase their probability of failure. In other word, large auditors (Big 4) enhance the quality of audit and reduce the likelihood of failure. As the regressor retains its statistical significant at 5% during three years before failure, it is an efficient predictor of the probability of failure. Audit modification (MODIFIED) is significant at a 1% level at t-1. The positive sign explains that finance companies which received a going-concern opinion or fundamental uncertainties in their audit report a have a higher likelihood of failure. Furthermore, TRUSTEE, which is given a value of one if one of the three specified trustees supervises the finance company and zero otherwise, is significant at 5% at t-1. It holds the significant level at t-2 with a positive sign for both years, which means that having one of the three specified trustees as a supervisor increases the risk of failure.

As explained earlier in section 4.3.2, four macroeconomic variables are used in the model. The macroeconomic variables, INFLAT, HPI and OCR are significant at 5% at t-1. The estimated coefficient of 2.822 for INFLAT with positive sign indicates that inflation increases costs and reduces finance companies’ profitability which results in a higher likelihood of failure. In addition, HPI indicates the increase in home loan interest rate, increase the probability of failure. In contrast, OCR with a negative sign shows the reverse impact of this variable on failure. When the official cash rate reduces, finance companies increase risk-taking. This leads to a higher probability of failure.

Table 5-8 Model 2

Variable	MDL 2-1	MDL 2-2	MDL 2-3
NUMDIR	0.168 (0.257)	0.081 (0.018)	0.050 (0.044)
DIRCHANGE	0.540 (0.109)	-0.854 (0.656)	-1.250 (1.433)
DIRAPPOINT	0.437 (0.291)	0.089 (0.025)	0.631 (1.943)
DIRRESIG	-0.108 (0.006)	0.555 (1.558)	-0.275 (0.284)
RELAT-TA	-2.318 (0.877)	0.162 (0.014)	0.417 (0.080)
BIGN	-2.798** (5.279)	-1.636** (5.273)	-1.715** (4.689)
MODIFIED	5.730*** (7.144)	19.087 (0.000)	21.539 (0.000)
AUDITLAG	0.011 (0.817)	-0.003 (0.386)	-0.005 (0.463)
AUDREM	-0.405 (1.055)	0.150 (0.349)	-0.048 (0.031)
TRUSTEE	1.571** (5.556)	0.665** (4.266)	0.591 (2.400)
AMDENDED	0.980 (1.277)	0.154 (0.013)	-0.278 (0.053)
AGE	-0.046 (1.817)	-0.029 (1.731)	-0.031 (1.496)
MEDIA	0.102 (1.265)	0.381 (1.251)	0.043 (0.035)
GDP	0.109* (2.599)	0.014 (0.274)	0.023 (0.818)
INFLAT	2.822** (3.797)	-0.163 (0.105)	-0.572 (0.446)
OCR	-1.296** (4.718)		
HPI	0.372** (4.823)		-0.124 (1.242)
Cons	-17.407* (3.003)	-0.749 (0.046)	1.805 (0.126)
MDL chi-square	47.849***	24.623*	24.716*
-2 LL	49.192	72.418	72.325
H&L	5.425	9.998	8.749
NagR^2	0.660	0.395	.397
Total class%	82.90	80.00	71.40

Number in parentheses is Wald Chi-square
*Significant at the 0.10 level
**Significant at the 0.05 level
***Significant at the 0.01 level

At t-1, the model, with Chi-square significance at 1% level and a total classification of 82.90%, shows the best result among Agency-related models. However, based on Hosmer-Lemeshow tests, all of the models are a good fit for the data and they seem to be a valid demonstration of the data. Models 2-1, 2-2 and 2-3 explain 66%, 39.50% and 39.7% of the variation in the data, respectively.

CAMELS and Agency-related Variables and Failure

Table 5-9 reports the logistic regression of the financial fail indicator results with the integration of both CAMELS and Agency-related variables. Due to the high number of variables in this category, macroeconomic and financial variable inserted in the model and Agency-related information was entered using the forward stepwise method.

TA-TL and TL-TE ratios, as measurements for capital adequacy, were significant over the three years of study, retaining a significance level of 5%. This shows that they have a high power of prediction. However, IMPAIR-TA, with a positive estimated coefficient of 40.843, is significant at 10% at t-2. This ratio represents assets quality and shows the higher the proportion of impairment assets, the lower the quality of asset. As the majority of finance company assets are loans and advances, the lower the quality of asset, the greater the likelihood of failure.

OE-OR and OE-TA, the management competency variables, are statistically significant at t-3. With a positive estimated coefficient of 8.676 at t-3, OE-OR suggests that the higher the proportion of operating expenses relative to operating revenue, the lower the management performance and the higher probability of failure. Moreover, OE-TA with an estimated coefficient of -3.648 at t-2 and -66.148 at t-3, explains that higher levels of operating expenses relative to total assets increase the possibility of failure. The negative sign of NETINT-TA reveals that the higher the company's interest income, the lower the likelihood of failure. Although failed companies have higher profitability (NPAT-TA), with an estimated coefficient of 19.347, the OCF-TA displays a lower cash flow which suggests accrual earnings management. OCF-TA, which denotes a measure of liquidity, shows a significant reverse relationship between liquidity and failure at t-2. In other word, the lower liquidity is, the higher the probability of failure.

Meanwhile, NPAT-TE is statistically significant with a positive sign at t-3, but the NPAT-TA and NETINT-TA coefficients with -27.352 and -31.399 explain the low earnings of institutions. The positive sign of NPAT-TE suggests the negative sign of equity which means that equity is in debt. Total asset is a proxy for company size. With an estimated coefficient of -5.703 at t-3, it suggests that size has a reverse impact on the likelihood of failure. In short, smaller size companies have a higher chance of failure.

BIGN is statistically significant and retains its significance at 5% during the three years before failure. This suggests that it is an efficient predictor of the probability of failure among finance companies.

Table 5-9 Model 3

Variable	MDL 3-1	MDL 3-2	MDL 3-3
TA-TL	0.043** (3.867)	0.034** (5.002)	0.070** (4.644)
TL-TE	3.392** (5.042)	3.035** (4.936)	7.068** (4.627)
IMPAIR-TA		40.843* (3.438)	
OE-OR			8.676* (2.949)
OE-TA		-3.648** (6.124)	-66.148*** (6.874)
NPAT-TE			6.390* (3.582)
NPAT-TA		19.347* (2.725)	-27.352 (2.222)
NETINT-TA		-29.983** (3.825)	-31.399 (0.772)
OCF-TA		-47.163*** (7.274)	
TA			-5.703* (3.698)
BIGN	-2.354** (5.084)	-2.028** (3.872)	-6.863** (4.456)
TRUSTEE	1.263* (3.736)		
INFLAT	3.064** (3.997)		-13.108** (4.876)
OCR	-1.136** (4.039)		
HPI			-2.068** (4.103)
Cons	-9.921 (0.532)	9.593 (1.106)	132.569** (4.511)
MDL chi-square	53.824***	49.536***	69.972***
-2 LL	40.386	46.104	24.238
H&L	2.408	4.235	2.461
NagR^2	0.729	0.683	0.857
Total class%	85.30	87.00	89.70

Number in parentheses is Wald Chi-square
*Significant at the 0.10 level
**Significant at the 0.05 level
***Significant at the 0.01 level

While similar to the results of the non-financial model, TRUSTEE, INFLAT and OCR are significant at t-1. Although INFLAT is significant with a positive sign (3.064) at t-1, which shows that high inflation increases costs and reduces profit and results in a higher chance of failure, this variable is negatively significant with an estimated coefficient of -13.108 at t-3. Simpasa (2010) claims that the inflation rate has a direct impact on bank power, meaning that growth in the inflation rate increases loan prices which leads to higher profitability and decreases the risk of failure.

The overall fit statistics (or log likelihood tests) are all significant. Under the Hosmer-Lemeshow tests, the null hypothesis is accepted. The models are a valid representation of the data. Meanwhile, the $NagR^2$ and total classifications of this model is higher than both the financial and non-financial models. Models 3-1, 3-2 and 3-3 explain 72.9%, 68.3% and 85.7% of the variation in the data, respectively.

5.8 Hazard Model

The hazard model results are presented in Table 5-10. As the second model in this study, the hazard model incorporates panel data from three consecutive years before failure. The hazard model is similar to logistic regression reruns – it contains on three different groups of variables to build three models. The first model only uses CAMELS variables (Model 4). The second model uses only Agency-related variables (Model 5). The third model includes both CAMELS and Agency-related variables (Model 6). In addition to the above variables, four macroeconomic indicators, Gross Domestic Product (GDP), Inflation (INFLAT), the Official Cash Rate (OCR) and House Price Interest Rate (HPI) are included in all of the models. The forward stepwise method (or likelihood ratio) is used to run Model 6 as it combines CAMELS and Agency-related variables.

As per Model 4, TL-TE and IMPAIR-TA are statistically significant at 10%. The positive sign of TL-TE, which represents a finance company's capital adequacy, suggests that higher levels of liability in relation to equity results in lower capital adequacy and a higher probability of failure. Meanwhile, IMPAIR-TA shows the high impairment loss which results in low asset quality and a higher likelihood of failure.

As presented in Table 5-10, among the non-financial variables in Model 5, BIGN, MODIFIED and AMENDED are statistically significant at 5% and TRUSTEE is significant at 10%. The negative sign of BIGN confirms that having a Big 4 as an auditor reduces the probability of failure. The positive sign of TRUSTEE reveals that the chance of failure increases if one of the three main trustee companies holds a supervision role in the finance company. Audit modified, with a positive sign, indicates that failed companies received more modifications in their audit reports compared to healthy companies. Additionally, significant audit modifications reveals that even though trustees were aware of breaches, they agreed to amend definitions in trust deeds - like changing the definition of related party transactions (Wilson et al., 2013). Therefore, the probability of a trust deed amendment is higher close to failure.

As a measurement of management performance, OE-TA is statistically significant at a 5% level when the financial and non-financial variables are integrated into the model (Model 6). The OE-TA coefficient estimate displays a negative sign which indicates higher operating expenses to total assets. This suggests lower levels of management performance and a higher likelihood of failure. OCF-TA, which represents a financial company's liquidity level, shows a significant reverse relationship between liquidity and failure. In other words, the lower the liquidity is, the higher the probability of failure. Total assets, which represents the company's size, with an estimated coefficient of -0.874, suggests that size has a reverse impact on the likelihood of failure. This means that smaller sized companies have a higher chance of failure.

As for non-financial variables, BIGN and AMENDED retain their statistical significance. This suggests that they are efficient predictors of the probability of failure among finance companies.

Table 5-10 Hazard Model

Variable	MDL 4	MDL 5	MDL 6
TL-TE	0.584* (2.994)		
IMPAIR-TA	11.346* (3.454)		11.965* (3.454)
OE-TA			-0.465** (3.228)
OCF-TA			-3.702* (3.714)
TA			-0.874** (4.344)
BIGN		-1.707*** (15.131)	-1.750*** (6.303)
MODIFIED		3.111*** (8.987)	
TRUSTEE		0.588* (3.616)	
AMENDED		1.746*** (9.184)	-1.750*** (6.303)
MDL chi-square	57.262***	73.929***	78.599***
-2 LL	130.126	115.306	108.789
H&L	8.958	4.535	1.871
$NagR^2$	0.407	0.500	0.532
Total class%	88.30	88.10	90.20

5.9 Model Evaluation

Model validation is an important step to evaluate both pieces of training sample and out-of-sample results. The results are provided in Table 5-11. The predictive power of the models was tested on 35 failed companies and 35 healthy companies as training samples. The study also included three failed companies and three healthy companies which failed after 2010, as an out-of-sample group. The coefficients of the fitted models are used to classify the out-of-sample results (Hosmer Jr, Lemeshow, and Sturdivant, 2013). The validation test assesses the accuracy of the models to discriminate between Fail and Healthy defaults in practice. The classification accuracy of all the models is summarised in Table 5-11. The table reports the predictive performance of the training sample and the out-of-sample or test sample. This classification table not only provides information about the accuracy of the model in predicting failure but also reflects embedded uncertainties in the model by Type I and Type II error.

Table 5-11 Classification Accuracy

	Training Sample			**Test Sample**		
	Type I Error	**Type II Error**	**Overall Accuracy**	**Type I Error**	**Type II Error**	**Overall Accuracy**
Model 1-1	18.92%	16.13%	82.40%	40.00%	0.00%	66.67%
Model 1-2	20.00%	10.34%	84.10%	25.00%	0.00%	83.33%
Model 1-3	16.67%	15.63%	83.80%	33.33%	33.33%	66.67%
Model 2-1	18.92%	15.15%	82.90%	40.00%	0.00%	66.67%
Model 2-2	21.62%	18.18%	80.00%	25.00%	0.00%	83.33%
Model 2-3	29.73%	27.27%	71.40%	40.00%	0.00%	66.67%
Model 3-1	14.29%	15.15%	85.30%	40.00%	0.00%	66.67%
Model 3-2	13.89%	12.12%	87.00%	**25.00%**	**0.00%**	**83.33%**
Model 3-3	**11.11%**	**9.38%**	**89.70%**	33.33%	33.33%	66.67%
Model 4	17.65%	11.17%	88.30%	25.00%	42.86%	61.11%
Model 5	29.17%	9.68%	88.10%	41.67%	33.33%	61.11%
Model 6	**17.39%**	**8.79%**	**90.20%**	**33.33%**	**16.67%**	**72.22%**

As can be seen in Table 5-11, the overall accuracy of Model 2, which included only non-financial variables, is between 71.40% at t-3 to 82.90% at t-1 among training sample. This accuracy level is lower than other logistic models for financial variables and the combination of financial and non-financial variables. It confirms that non-financial variables are not sufficient and reliable enough on their own for prediction purposes. The in-sample classification of Model 1, which is based on financial variables, shows enhancement in the overall accuracy performance. At t-2, this Model with an overall accuracy of 84.10% and the lowest type II error of 10.34%, has the best results in comparison with t-1 and t-3. However, the results show that Model 3, with the integration of financial and non-financial variables, has a significantly higher performance level, especially during the t-3 period, with correct classification of 89.70% and the lowest percentage of 11.11% and 9.38% for Type I and Type II errors respectively. Moreover, at t-2, this Model indicates better results with total accuracy of 87.00% and type II error of 12.12%.

Models 4, 5, and 6 which use a hazard model, are superior in discriminating between failed and healthy companies. Model 4, which included only financial variables correctly classifies 88.30% of the training sample and is better than logistic Model 1 for financial variables during the three years before failure. While classifying 88.10% of failed and healthy companies correctly, Model 5 performs better than Model 2 for non-financial variables. Model 6 has the highest accuracy of 90.20% overall and the lowest Type II error of 8.79%. It is thus the best model for predicting failure among financial companies.

Regarding out-of-sample performance, all of the logistic models at t-2 have the best performing results. The highest correct classification of 83.30% for Models 1, 2 and 3 at t=2, with the lowest percent (25%) for Type I errors and zero percentage of Type II errors are superior in discriminating between Failed and Healthy companies.

At t=1, all of the models correctly classify 66.67% of the out-of-sample failures. They show a similar rate of misclassification (40.00% for false positive and zero percent of false negative). They do not show any Type II misclassifications. There is a 40% chance for Type I errors for financial, non-financial and a combination of both groups of variables at t-1. This is the highest error rate among the logistic models. At t=3, Model 1 and Model 3 have the same overall classification of 66.67% with Type I and Type II errors equal to 33.33%. This indicates that both of these models are worse in terms of predicting true defaults. These models are the only models with Type II errors among logistic models.

Of the hazard models, with an overall accuracy of 72.22% and Type I errors of 33.33% and 16.67% Type II errors, Model 6 provides the best predictor of out-of-sample failures.

The overall results of the classification matrix indicate that Model 6 and 3-3 which were developed based on financial and non-financial variables are the best performing models for in-sample data. These models perform better than the rest of the models in terms of correct classification. In addition, these models have the lowest Type II errors (of 8.79% and 9.38% respectively). In term of out-of-sample, Models 6 and 3-2 perform the best with highest overall classification. Although Model 2-2 has the same level of accuracy as Model 3-2, it is not reliable to predict failure solely based on non-financial information. In addition, even though Model 1-2 also has the same level of accuracy, Model 3-2 has higher in-sample performance and thus beats Model 1-2.

As explained earlier, error tables show the accuracy of the model for a single cut-off point which, in this study, is 0.5. AUC, Gini, KS and H measures are used to measure the discriminant power of the models in this study.

The predictive accuracy based on the AUC, Gini, KS and H statistics shows different results from different preference. Table 5-12 displays the summary of all four measurements for all the models. Figure 5-1 presents the contrast more clearly.

In the first comparison, of models in group 1 and models in group 2, the results show the overall classification accuracy of Model 1 (with financial variables), is better than Model 2 (with non-financial variables). The Gini coefficients for Models 1-2 and 1-3 are 0.75 and 0.76 at t-2 and t-3 compared to 0.66 and 0.63 in Models 2-2 and 2-3 in the same timeframe. However, the Gini and AUC coefficients at t-1 in Model 2 are slightly better than Model 1 which is in line with the results of the error table.

The Gini increases from 0.80 to 0.88 at t-1 and from 0.76 to 0.95 at t-3 when non-financial variables are added to the financial variables in Model 1. In addition, KS has a larger maximum distance between the cumulative healthy companies' score and fails' score in Model 3-3 (0.85) which leads to larger Gini coefficients. The AUC, Gini and KS show the superior classification accuracy of Model 3 at t-3 in comparison to the other logistic models.

Opposed to the accuracy of the hazard model in the error table, the discriminant power of this model is inferior when compared to Model 3. The Gini coefficient and KS of Model 6 is (0.95-0.74 = 0.21) and (0.85-0.61 = 0.24) are less than Model 3-3 respectively.

On the other hand, by assuming the same H cost distribution (cost weight), the performance of Model 3 at three years before failure is 0.82, while the hazard model is 0.33. Therefore, concerning the H measure, once again, Model 3 (which integrates financial and non-financial variables) has the best discriminative power, while the hazard model has the worse one.

Table 5-12 Predictive Accuracy

In sample

	H	AUC	Gini	KS
Model 1-1	0.5733	0.9039	0.8078	0.6450
Model 1-2	0.5556	0.8767	0.7535	0.6571
Model 1-3	0.6109	0.8849	0.7698	0.6857
Model 2-1	0.5906	0.9167	0.8335	0.6571
Model 2-2	0.4704	0.8318	0.6637	0.6286
Model 2-3	0.4312	0.8196	0.6392	0.5143
Model 3-1	**0.6915**	**0.9437**	**0.8874**	0.7628
Model 3-2	0.6790	0.9277	0.8555	0.7689
Model 3-3	**0.8214**	**0.9792**	**0.9584**	**0.8502**
Model 4	0.2506	0.7816	0.5633	0.5257
Model 5	0.4415	0.8924	0.7848	0.6400
Model 6	0.3329	0.8724	0.7448	0.6171

Overall, the performance of the logit model with financial variables is better than the performance of the logit model with only non-financial variables. However, the logit model that combines both the financial and non-financial variables outperforms the models which only use one group of variables. In general, the discriminative power of the hazard model, as opposed to the error table, is weaker than the logit models.

The discriminant power of out-of-sample results is not reliable due to the small sample size. The study only includes three failed companies and three healthy companies.

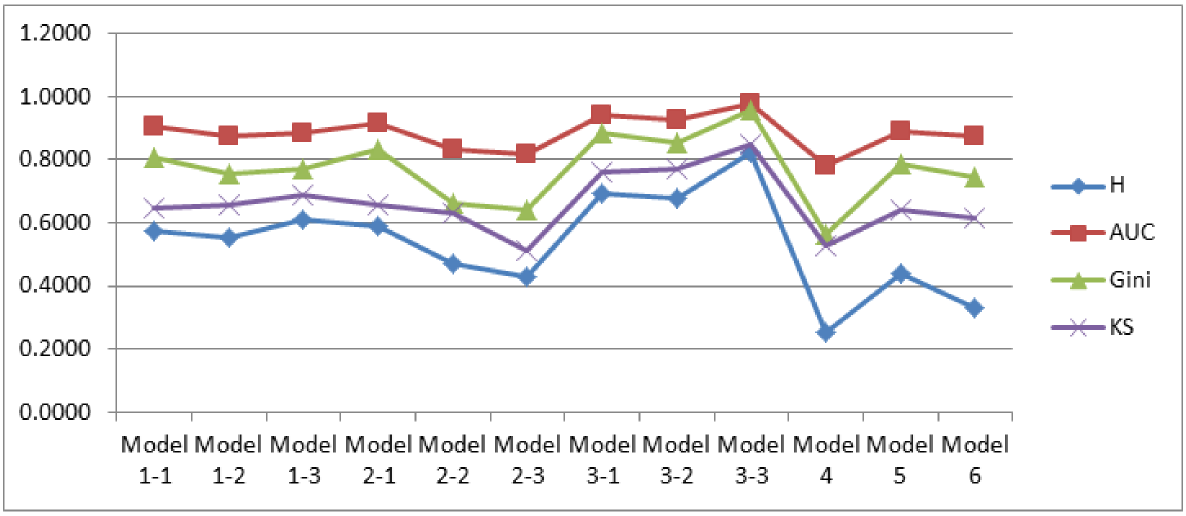

Figure 5-1 Model Performance

5.10 Summary

This chapter has provided detailed information about the process of data analysis and described the study's main findings. It has included information on data mining and missing data. It has discussed each of the descriptive statistics and variables used in this study. The chapter has provided a summary of the univariate analysis, which has been used to compare the mean and median value through student t-test for all of the parametric variables. It has also explained the Mann-Whitney U test which has been used to check the non-parametric variables. This chapter has explained the processes of correlation analysis and Spearman's rank correlations, which have been used to assess the nonparametric variables and panel data for three years. The chapter has provided a detailed discussion of the logistic regression and hazard model results and the specific variables that contribute to the successful prediction of failure. It concluded by outlining the methods used to test the models' discriminative power.

Chapter 6

Conclusion

6.1 Introduction

Having explained the data analysis and finding, Chapter 6 provides a summary of the whole study. It begins with an overview of the study and is followed by Section 6.2, which presents a detailed discussion of the results. It provides a summary of the findings, which highlights conclusions drawn from the analysis undertaken. The chapter concludes by outlining the study's limitations and suggesting avenues for future research.

6.2 Overview of the Study

In New Zealand, the number of finance companies, especially the number of non-bank deposit takers increased rapidly, between 2000 and 2007 (Commerce Committee, 2011). After 2004, banks extended their credit lending into the property sector. This means that finance companies' coverage shifted to the riskier territory, including second-hand cars and consumer purchases. The lack of an efficient regulatory system and prudential supervision led to the failure of over 31 finance companies during a four year period, between 2006 and 2009. It was a huge shock to the New Zealand market, with an estimated loss of more than NZ$3 billion (Commerce Committee, 2011). These collapses affected around 150,000 and 200,000 investors (Douglas et al., 2014). Following the failure of these finance companies, scholars sought to determine the causes and attribute blame (Kabir and Laswad, 2014; Yahanpath and Cavanagh, 2011). While some scholars reviewed the New Zealand banking regulations (Tripe, 2012; Wilson, 2009) others focused on individual factors like related party transactions (Bhuiyan and Roudaki, 2018; Wu and Malthus, 2012), impairment assets (Kabir and Laswad, 2014) or audit failures (Kabir, Su, and Rahman, 2016). What has remained largely unexplored in these studies is how investors could have determined the risk of investing in these companies, prior to failure.

The primary aim of this study was to determine the underlining variables that contributed to the failure of finance companies. The material was sourced for three years prior to the finance companies' failures. The data has been used to determine the best model for predicting failure.

The first group of variables used in this study are the CAMELS variables or the financial ratios used to measure capital adequacy, asset quality, management competency, earnings, liquidity and size.

Each of the six elements of financial soundness indicators plays a different role in the stability assessment. As the first indicator, capital adequacy is used to measure a financial institution's capacity to maintain sufficient levels of capital to absorb any losses (Pilbeam, 2005). As the risk of failure often arises from impairment of assets, the quality of asset portfolios is measured with asset quality ratios (Grier, 2007). Management quality is used to evaluate management's ability to ensure the efficiency and stability of the company. The next indicator is earning quality. This not only reflects the business' ability to generate profit but also may influence earning sustainability (Dang, 2011). The bank's capacity to fulfil its obligations is measured by liquidity. Size of the finance company is the last financial variable in this group.

Balcaen and Ooghe (2006) explain that it is not advisable to rely just on financial information when predicting failure as it is vulnerable to manipulation. The introduction of non-financial information can offset the risk of manipulation. Therefore, this study included certain aspects of Agency-related information, like board characteristics, related party transaction, audit quality, trusteeship, firm age and media. The board of directors has two key responsibilities; advising and monitoring (Adams and Ferreira, 2007). Previous literature has discussed the board of directors in terms of the relationship between board size (the number of members) and firm performance (Dalton and Dalton, 2005; Guest, 2009). Although Kyereboah-Coleman and Osei (2008) argue that a higher number of directors provides more alternative forms of leadership and lessens the probability of CEO authority (Bassem, 2009), Pathan et al. (2007) state that smaller boards of directors are more effective in monitoring managers and increase firm profitability. Thrikawala (2016) contends that the optimal board size is dependent on the board's specific responsibilities and the company's strategic direction.

The other aspect of non-financial information is related party transactions. Non-disclosure or incorrect disclosure of related party transactions in financial reporting can significantly misstate the financial position and performance of the company. Misleading investors about related party transactions is management fraud and is often hard to detect (Wu and Malthus, 2012). It is, therefore, one of the key factors identified by accounting standards and a key focus of new regulation.

Another aspect of agency information is auditing, which plays a key role in protecting investors and ensuring the credibility of financial statements. Auditors assess the entity's going-concern ability based on financial information and management plans. A modified audit report works as a 'red flag,' and is associated with a higher chance of failure (Carson et al., 2013). As a proxy for audit quality, audit fees are also important and are considered in this study (Francis, 2004). Francis and Yu (2009) found that large auditors like the Big 4 are more likely to issue going-concern reports because larger audit firms suffer a higher reputational loss from inaccurate reporting. Furthermore, a longer lag between the end of the financial year and the audit sign-off date could suggest negotiation between the auditor and company, or indicate more work involved in uncovering financial irregularities (DeFond et al., 2002). Therefore, in this study, audit reports, audit fees, audit size and audit lags have all been considered as aspects of audit quality.

Trustees play an important supervision role in New Zealand, as the Reserve Bank delegated the surveillance of NBDTs to trustee companies. They have a fiduciary duty to ensure that prudential requirements are included in trust deeds (Wu and Malthus, 2012). Therefore, the Reserve Bank relies on trustees to report any instances of non-compliance, including breaches of trust deeds' terms and conditions. Thus, trust is another Agency-related variable included in this study.

Dyck et al. (2010) state that failure prediction relies not only on corporate governance, like auditors and trustees as internal supervisors but also on several non-traditional, external players, like media. As Miller (2006) explains, the press has exposed many fraudulent schemes. This study, therefore, considers the press coverage of failure serves to shed lights on the underlying public's view.

Agrawal and Gort (2002) found that mature companies have more experience and knowledge gained over time. Maturity creates a reputation and builds faith among investors. However, maturity can also lead to rigidity, inactivity and a reluctance to change (Loderer and Waelchli, 2010) which ultimately diminish a company's performance and may cause them to fail. Thus, this study also included firm maturity as an Agency-related variable.

Macroeconomic variables (Gross Domestic Product, Inflation, the Official Cash Rate and the House Price Interest Rate) were also included in this study.

The study used a sample of 35 failed financial companies (between 2006 and 2010) which were uniquely matched based on asset size, with the same number of healthy finance companies. Data were collected for three consecutive years before failure and matched with healthy companies' data for the same period.

Logit and hazard models were used to identify the most suitable model for prediction. This study focused on predicting the probability of failure by using as many variables as possible. In order to avoid the problem of overfitting, the developed models were based on three different variable categories. The first model incorporated only CAMELS financial variables. The second model used only Agency-related variables. The third model included both CAMELS and non-financial variables.

The study tested the accuracy of these models using out-of-sample data collected from financial institutions which failed after 2010 (new regulations were implemented in 2009). Error tables, AUC, Gini, KS and H measures were used to assess the models' performances.

6.3 Discussion of the Results

The study examined three main research questions and nine sub-questions using univariate analysis, nine logistic models and three hazard models. Models 1-1, 1-2, 1-3 and Model 4 included only financial variables to test whether CAMELS-based ratios can predict failure or not. The second group of models (2-1, 2-2, 2-3 and Model 5) were created based solely on Agency-related information to test whether Agency-related information alone can predict failure. Models 3-1, 3-2, 3-3 and Model 6 were constructed based on combined financial and non-financial information to test whether the integration of the two groups of variables can predict failure among New Zealand finance companies.

6.3.1 CAMELS-based Ratios

CAMELS rating ratios underpin the financial ratios in this study. As the first indicator, capital adequacy has four proxies in this study. Total equity to total assets (TE-TA) was highly correlated with total assets to total liquidity (TA-TL) and eliminated from the models. TA-TL and total liability to total equity (TL-TE) were found to be statistically significant and retained their significant levels in logistic models over the three years before failure. In addition, TL-TE was also found to be significant in the hazard model. The results were consistent with the outcomes from the univariate analysis. Although the z-score for TA-TL was only significant at t-1, the median value of TA-TL is always higher in healthy companies.

Moreover, the mean value of TL-TE was nearly three times more among failed companies during the three years prior to failure even though the t-stat was only significant at t-2. Dang (2011) declares that sufficient capital levels balance credit risks and market risk exposure. It ensures that institutions can weather any losses during periods of crisis (Ongore and Kusa, 2013; Pilbeam, 2005). Capital adequacy ratios suggest that failed companies have lower capital relative to healthy companies. This argument is in line with CAMELS theory. The outcome is also in line with previous research which argues that capital adequacy significantly affects commercial banks performance in Kenya and the United States (Ongore and Kusa, 2013; Cox et al., 2017). The result is similar to Douglas et al.'s (2014) findings which showed failed companies have worse capital adequacy than non-failed ones among New Zealand finance companies.

Loan and advances are a financial company's main assets. A company's loan portfolio quality determines the profitability and performance of the company. Hence, finance companies' greatest risk comes from unpaid loans (Dang, 2011). The results show that impairment assets to total assets (IMPAIR-TA) were statistically significant at t-2 and t-3 in the logistic regression models and also in the hazard model. The high estimated coefficient of 101.660 at t-3 demonstrates a high proportion of impairment assets to total assets among failed companies.

Additionally, the univariate test shows significant z-score at t-3, indicating a significant difference in the median value of failed and non-failed companies. Therefore, the results show a high portion of nonperforming loans among failed companies, demonstrating low quality asset and consequently low company performance which is in line with CAMELS theory. The result is supported by King, Nuxoll, and Yeager (2006) who explain that asset quality is lower for failed banks. Moreover, Sangmi and Tabassum (2010) analysis of Indian commercial bank financial performance concluded that asset quality directly impacts bank performance. The outcome is similar to previous studies on failed New Zealand finance companies (Douglas et al., 2014; Kabir and Laswad, 2014).

Grier (2007) contends that management is the most important factor in the CAMELS rating system as it plays a vital role in a company's success. Although management efficiency can be captured by the quality of other CAMELS elements, in this study operating expenses to operating revenue (OE-OR) and operating expense to total assets (OE-TA) are chosen as proxies for measuring management competency. OE-OR was found to be statistically significant at t-3, and the estimated coefficient of 4.359 reveals that failed financial companies have a higher portion of expenses that could not generate enough income. Also, OE-TA was negatively significant during the three years before failure. The negative sign presents the reverse relationship of this ratio, with a higher probability of failure. It is obvious that a high proportion of impairment asset increases operating expenses and reduces company capital and its net profit. This outcome shows inefficient management strategies among failed finance companies. This is in line with CAMELS theory. As Ongore and Kusa (2013) have previously argued, management efficiency significantly affects the financial performance of (Kenyan) commercial banks. In their study of Indian banks, Sangmi and Tabassum (2010) note that management efficiency directly impacts financial performance.

Consistent earnings not only build public trust by demonstrating a business' ability to generate profit but also absorbs any loan losses and influence earnings sustainability (Dang, 2011; Grier, 2007). As shown in Table 6-1, NPAT-TE and NPAT-TA were both found to be statistically significant at t-3. The estimated coefficient of -23.393 for NPAT-TA at t-3 and -32.194 for NETINT-TA at t-2 indicating a huge loss incurred in net earnings and net interest movement by finance companies. This is the result of enormous impairment losses. These results are consistent with the univariate tests which show that the NPAT-TA and NETINT-TA of the failed companies are lower than healthy companies, which is in line with CAMELS theory. However, the high NPAT-TA at t-2, while having low net interest income (NETINT-TA) and low cash flow (OCT-TA), could be suggestive of accruals earnings management. When a loan is impaired and an impairment loss is recognised, either the receipt of interest revenue and principle from the borrower would be expected to be less, or the recovery would be delayed. Therefore, an impairment loss is likely to be an indicator of future cash flow problems and a sign of financial distress (Kabir and Laswad, 2014). Ongore and Kusa (2013) conclude that banks with high asset quality and low non-performing loan are more profitable. As Keovongvichith's work (2012) on the Laotian banking sector during 2005-2010 shows, though the banks' earning ability (net income/total assets) has a declining trend, they always managed to generate 2 or 3% on an aggregate basis and resisted failure. However, he notes that some international banks record a ROE of 10%. Low asset quality (IMPAIR-TA) decreases company profitability and increases the risk of failure. This can be concluded because the failed companies have inferior earnings quality than their healthy counterparts which is in line with CAMELS theory.

Table 6-1 CAMELS Based Models

Variable	MDL 1-1	MDL 1-2	MDL 1-3	MDL 4
TA-TL	0.036**	0.030**	0.033**	0.006
GLOAN-TA	-0.096	1.534	-0.954	-1.204
TL-TE	3.485**	2.749**	3.978**	0.209**
IMPAIR-TA	22.216	48.582**	101.660*	2.372**
DOUT-GLOAN	19.342	40.333	-166.300	15.831
OE-OR		-0.149	4.359**	-0.071
OE-TA	-1.066*	-3.645***	-40.985***	-0.133
NPAT-TE	0.802	1.928	3.243*	0.245
NPAT-TA	-5.335	16.953	-23.393**	-0.506
NETINT-TA	-3.947	-32.194**	-1.577	-2.824
CA-TA	0.925	-0.030	-1.303	1.451
OCF-TA	0.648	-40.858***	11.771	-1.672
TA	-1.495**	-1.370*	-3.611***	-0.604

A lack of liquidity can seriously affect profitability and confidence, and increase the probability of failure (Keovongvichith, 2012). Liquidity reflects the bank ability to meet its financial commitments in a period of crisis without incurring undesirable losses. Therefore, maintaining a balance between short term assets and short term liabilities is vital for finance companies (Douglas et al., 2014). However, as presented in Table 6-1 the OCF-TA is negatively significant at t-

2. In short, the lower the ratio, the lower liquidity is, which ultimately means a higher chance of failure. This result is contrary to Ongore and Kusa's (2013) finding that liquidity has no significant effect on bank performance in Kenya, particularly when the strong management strategies generate more income and boost bank performance by investing in liquid assets. Keovongvichith (2012) notes that the Laotian banking sector keeps more than 50% of their total assets in liquid form. Hence, it proves the operation of the bank will be stable in future. The results of this study are in line with the CAMELS theory and prove that failed finance companies have low liquidity levels compared to healthy companies. It is also reinforced by earlier studies which found that failed companies have lower cash flows than healthy companies (see Douglas et al., 2014).

Size of a finance company is the last financial variable in the CAMELS-based ratio. Table 6-1 demonstrates that SIZE is negatively significant during the three years before failure; this finding is in line with CAMELS theory. It is also consistent with the univariate tests which show the mean value of size is higher among healthy companies than failed companies, even though it was only significant at t-1. This result is consistent with earlier studies (Lanine and Vennet, 2006), which found that size is negatively related to failure and associated with the concept of 'too big to fail.' The failed New Zealand finance companies were smaller than the healthy ones. However, as Van Peursem and Wells (2001) note, 'large' New Zealand companies are comparatively small internationally, due to the country's size. As this study focuses only on New Zealand companies, this does not present a problem.

Overall, the results support the first research question and indicate that financial information (CAMELS-based ratios) can predict failure among finance companies. Importantly, it also indicates investors may have been able to infer from published information which finance companies were likely to fail three years in advance.

6.3.2 Agency-related Information

Corporate governance is associated with an organisation's internal performance and includes a set of regulated principles between the institution's board of director, managers, its shareholders and stakeholders (OECD, 2004) to ensure the organisation achieves its goals (BBVA Microfinance Foundation, 2011). Aspects of Agency-related information are used as non-financial information in this study. The results included in Table 6-2 are discussed in the following paragraphs.

There are four proxies for board composition in this study, NUMDIR, DIRCHANGE, DIRAPPOINT and DIRRESIG. The results, summarised in Table 6-2, show an insignificant relation between board composition and failure. It is consistent with univariate tests which show no difference in variables' mean values between failed and non-failed companies at t-1 and t-2. However, the table shows significant differences in mean values and median values of DIRCHANGE, DIRAPPOINT and DIRRESIG at t-3. These results are due solely to one failed company that appointed seven directors and had six directors resign at t-3. In general, these variables were not statistically significant. The results are consistent with prior literature that suggests managers tend to stay and manage important financial metrics to conceal financial difficulties from investors (Schilit and Perler, 2010). Although Thrikawala (2016) suggests that large boards improve the performance and reduce the failure possibility of finance companies in Sri Lanka and India, the results are similar to Jaikengkit (2004) who suggests that board size and the probability of financial distress are not linked in Thailand's financial institutions. It is also consistent with Chin et al.'s study on 426 annual observations of New Zealand firms, which found no significant relationship between board size and firm performance. The results for DIRCHANGE, DIRAPPOINT and DIRRESIG also find support in Douglas et al.'s (2014) work. They note an insignificant relationship between director turnover and failure. Therefore, there is no significant difference in the board composition of failed and non-failed finance companies. This finding contradicts agency theory.

RELAT-TA and RELAT-GLOAN included in Table 6-2 are proxies used to measure the rate of related party lending. RELAT-GLOAN was eliminated from the model because of high correlation with RELAT-TA. Although RELAT-TA was statistically insignificant, meaning there was no relationship found between related party lending and failure, the univariate tests show that mean and median values of RELAT-TA and RELAT-GLOAN are higher among failed companies than non-failed companies in the three years prior to failure. The outcome is not in line with stewardship theory. The reason could be due to not disclosing or incorrect disclosure of related party information in financial statements. This was notable by checking the comparative figures during data collection which was also supported by Wu and Malthus (2012). For instance, company X shows a value for related party lending at t-2 with a comparative figure for t-3, however, fails to disclose related party lending in t-3 financial statements. In another scenario, the comparative figures in the annual report of company Y may not be matched with the original figures in the annual report for the previous year. The insignificant result is supported by Douglas et al. (2014) who studied failed New Zealand finance companies and found no relationship between related party lending and failure. However, as Barker and Javier (2010) have noted, New Zealand finance companies have the highest level of related party transactions in the NBDT sector; this is especially true when firms have interlocking directors on the board (Bhuiyan and Roudaki, 2018). Wu and Malthus (2012) who studied the role of related party transactions in the failed New Zealand finance companies found that related party transactions were higher in such companies and significantly related to their failure.

This study also evaluated audit quality. As shown in Table 6-1, Audit Big was found to be statistically significant and retained its significant levels over the three years in both the logistic regression and hazard models. The negative sign of the variable explains that failed companies have a lower likelihood of nominating a Big 4 auditor compared to healthy companies. This finding is consistent with the univariate test, which shows that the mean value for electing Big 4 is higher among healthy companies. The result is similar to Francis (2004) who argued that audit quality is dependent on audit firm size. Prior literature proves that in the event of company failure, auditors are one of the first groups to be questioned. As the Big 4 all have reputations to protect, they are providing high quality audits. Chiang and Prescott (2010) reveals a pattern between audit firms and failed finance companies and suggest that either finance companies may have purposely decided not to engage the services of a large audit firm, or whether the auditor declined to be associated with the finance company.

Moreover, modification report (MODIFIED) was found to be significant at t-1, meaning failed companies received more modified reports at t-1 rather than non-failed companies. However, it is important to note that only one finance company received a qualified report and 17 companies received unqualified reports with 'fundamental uncertainties' or 'emphasis of matter' paragraphs in their audit reports. This shows that the audits of these failed companies were not thorough and lacked in-depth analysis. Vaughan (2009) believes that if auditors had issued qualified opinions, this would have provided trustees with a red flag and encouraged them to intervene at an earlier stage AUDLAG and AUDREM are not significantly related to the failure of the finance companies. The insignificant result of AUDREM is consistent with Li (2009) who suggests that there is no statistically significant association between audit fee and audit quality. AUDLAG also does not show a significant relationship with failure which that can be related to different aspects of the audit firm and audit committees of such companies. For instant, Sultana, Singh, and Van der Zahan (2015) indicate that audit lag is influenced by audit committee experience and prior audit firm. Expert audit committees with great knowledge and assurance in negotiations with the external auditors and mediating auditor disagreements can reduce overall audit lags (Sultana et al., 2015). However, if an auditor has worked with a client for a couple of years, they have enough knowledge about their business and they are familiar with the company position; this ultimately reduces the audit lags. Therefore, more information is needed to evaluate the impact of audit lag on finance company failure. The significant relationship between BIGN and MODIFIED indicates that failed companies have inferior audit quality, an argument supported by agency theory.

Trustee companies play an important fiduciary role as the Reserve Bank delegated the supervision of NBDTs to them. The TRUSTEE variable focuses on three main trustee companies, which account for the majority of the sample. As shown in Table 6-2, failed companies are more likely to have one of the three main trustee companies, rather than the non-failed companies. This finding is consistent with Douglas et al.'s (2014) work. It also echoes concerns raised by both the International Monetary Fund (2014) who stated that trustees were not performing their role adequately and the Commerce Committee (2011) who argued that trustee companies need to have expert and qualified staff to understand the nature of the finance sector and specific industry risks. Although AMENDED was not significant in the logit model, it was found to be significant in the hazard model. Univariate tests show significantly different mean values on Trust deed amendments between failed and non-failed companies. Most of the amendments are minor and do not focus on the debt covenant restrictions (Douglas et al., 2014). Wilson et al. (2013) note that even if the trustee were aware of the breaches, they agreed to amend the definitions in the trust deeds like change the definition of related party transaction. In short, failed finance companies have lower trustee characteristics than healthy companies; this finding is in line with agency theory.

Table 6-2: Agency-related Models

Variable	MDL 2-1	MDL 2-2	MDL 2-3	MDL 5
NUMDIR	0.168	0.031	0.050	-0.232
DIRCHANGE	0.540	-0.854	-1.250	0.714
DIRAPPOINT	0.437	0.089	0.631	0.098
DIRRESIG	-0.108	0.555	-0.275	-0.180
RELAT-TA	-2.318	0.162	0.417	0.354
BIGN	-2.798**	-1.636**	-1.715**	-1.707***
MODIFIED	5.730***	19.087	21.539	3.111***
AUDITLAG	0.011	-0.003	-0.005	-0.002
AUDREM	-0.405	0.150	-0.048	-0.070
TRUSTEE	1.571**	0.665**	0.591	0.588*
AMDENDED	0.980	0.154	-0.278	1.746***
AGE	-0.046	-0.029	-0.031	-0.024
MEDIA	0.102	0.381	0.043	0.090

AGE is considered as the years between when a firm began operations and the year of data submission (Microfinance Information Exchange, 2007) or the data collection year. Although the result (Table 6-2) shows a statistically insignificant relationship between firm maturity and failure in the models, the univariate tests display a high difference in mean values of failed and non-failed companies in the prior three years before failure. The outcome suggests that healthy companies have served in the market nearly two times more than failed companies; this finding is in line with agency theory. The results are similar to Nurmakhanova et al. (2015) who concluded that finance company maturity positively affects financial sustainability. As Caudill et al. (2009) note, mature firms generally control costs more efficiently which leads to higher profitability.

Media is an extra-legal institution that plays a critical role in forming public thoughts (Cohen et al., 2017). As presented in Table 6-2, MEDIA is statistically insignificant in the three years prior to failure. The univariate tests do not indicate a considerable difference in mean values of failed and healthy companies. Although Miller (2006) believes that the media, especially the business press, plays a key role in regulating financial institutions, this study has found no results to support this argument. In this study, media only reported on failed finance companies just before they announced that they were going into receivership. Most of the reporting was about related party transactions, interpreting companies' financial situations and assigning blame. Although it is not compulsory for finance companies to publish their financial reports, annual information and financial reports are accessible through the companies' office. In addition, media could act as a whistle blower who discloses misconduct carried out by the managers on individuals in the finance company. Price Waterhouse Cooper (PWC) announced the positive contribution of the whistle blowers and highlighted more than 36% of economic crimes are detected by whistle blowers (Rachagan and Kuppusamy, 2013). However, the media performed very weak and kept quiet till close to the event. Even though (Dyck et al., 2010) explains that we cannot expect the media to act as a monitor for small companies, the loss of more than NZ$3 billion dollars in New Zealand in a total share market of only NZ$75 billion is not negligible. In conclusion, there is no difference in media citations between failed and healthy companies. This finding contradicts Agenda-setting theory.

Overall, the outcomes support the second research question and suggest that non-financial information (Agency-related information) can be used to predict the risk of failure among finance companies. However, a reduction in the degree of freedom from having too many variables in models with a small sample size may be the reason that other variables are not significant (Douglas et al., 2014).

6.3.3 CAMELS-based Ratio and Agency-related Information

Financial and non-financial variables were integrated to develop the third group of models to determine whether the combination of both groups of variables can enhance predictive abilities.

Table 6-3 shows the results for the combined models for logistic regression for the three years prior to failure and also for the hazard model. It is clear that TA-TL, TL-TE, which were significant in Models 1-1, 1-2 and 1-3, retain their significant levels in the combined variables models during the three years before failure. The comparison proves that these ratios are efficient predictors of the probability of failure. It is also similar for BIGN which holds the significant level for all three years, the same as Models 2-1, 2-2, 2-3 and 5.

Similar to Model 1-2, Models 3-2 and 6 show that low quality assets (IMPAIR-TA) increase operating expenses (OE-TA). This results in low earnings (NETINT-TA) and poor cash flows (OCF-TA). NPAT-TA is significant in Model 3-2 opposed to Model 1-2. The high NPAT-TA of 19.347, in the condition of high operating expenses, low net interest income and low cash flow indicates accrual earnings management. In addition, by knowledge of high impairment loss at t-3, which is significant in Model 1-3 but not in Model 3-3, it leads to high operating expenses and results in high OE-OR and OE-TA. OE-OR, with a positive sign, shows a direct relationship with failure and OE-TA displays a negative relationship with failure. Model 1-3 shows NPAT-TA of -23.393 which is due to a huge company loss while TL-TE of 7.068 in Model 3-3 indicates low levels of equity; hence the ratio of net profit (NPAT) to total equity (TE) results in a high positive coefficient. Moreover, TA is negatively significant in Model 3-3 and Model 6, and TRUSTEE is just positive and significant in Model 3-1.

Table 6-3 Combined Variables Models

Variable	MDL 3-1	MDL 3-2	MDL 3-3	MDL 6
TA-TL	0.043**	0.034**	0.070**	
TL-TE	3.392**	3.035**	7.068**	
IMPAIR-TA		40.843*		11.965*
OE-OR			8.676*	
OE-TA		-3.648**	-66.148***	-0.465**
NPAT-TE			6.390*	
NPAT-TA		19.347*		
NETINT-TA		-29.983**		
OCF-TA		-47.163***		-3.702*
TA			-5.703*	-0.874**
BIGN	-2.354**	-2.028**	-6.863**	-1.750***
TRUSTEE	1.263*			
AMENDED				2.230***

Tables 5-11 (classification accuracy) and 5-12 (discriminative power) present the findings for the third research question. The overall accuracy of in-sample is higher in Model 6. Model 3-3 has the best result, indicating that the combination of financial and non-financial variables produces a better in-sample prediction. However, as per discriminative power table, Model 3-3 has higher AUC, Gini, KS and H measures and thus outperforms Model 6. Therefore, due to higher in-sample accuracy and lower Type I and II errors, one can conclude that Agency-related information can improve the ability of failure prediction than CAMELS ratios alone.

However, the out-of-sample accuracy percentages do not suggest any differences between Models in group 1 (Model 1-1, Model 1-2, Model 1-3), group 2 (Model 2-1, Model 2-2, Model 2-3) and group 3 (Model 3-1, Model 3-2 and Model 3-3). The overall accuracy of the models for the three groups has similar percentages of 66.67%, 83.33% and 66.67% at t-1, t-2 and t-3 respectively. Furthermore, Type I error is 40.00%, 25.00%, and 33.00% in one, two and three years before failure correspondingly. However, type II errors are 0% at year one and year two in advance and also at t=3 in Model 2-3. Whereas, Model 1-3 and Model 3-3 have 33.33% Type II errors at three years before failure. The R project could not calculate the AUC, Gini, KS and H measures due to the small size of the out-of-sample cases. Therefore, any discussion of out-of-sample results is deemed to be unreliable.

6.4 Summary of Findings

The overall results indicate that there is sufficient evidence to support all three study objectives. The first objective focused on the CAMELS-based ratios and the ability of financial ratios in predicting finance company failure. The results have confirmed that financial soundness indicators are inferior among failed finance companies from three years before failure. The stable level of significance for some of the ratios, like total assets to total liquidity (TA-TL), total liability to total equity (TL-TE), operating expenses to total assets (OE-TA) and total size (TA) for the three years prior to failure confirm that failed finance companies have inferior financial based ratios than healthy companies. Significantly, most of the variables are statistically significant at three and two years before failure. Therefore, the predictive power of the model is higher at t-3 and t-2. This finding is supported by substantial differences in asset quality ratios, like impairment assets to total assets (IMPAIR-TA) and operating expenses to total assets (OE-TA) as management competency at t-3 and t-2. The main reason is that the majority of related party loans and advances were written off in the two years prior to failure. This practice directly affected earnings quality related ratios, like net profit after tax to total assets (NPAT-TA) and net profit after tax to total equity (NPAT-TE). Although previous literature has found significant differences between failed and non-failed companies one year before failure, this study has shown that significant differences are noticeable even earlier; two and even three years before failure.

The second objective was dedicated to Agency-related variables and the ability of non-financial variables in predicting financial company failure. Auditor characteristics and trusteeship are significant variables in this category for both the logit model and the hazard model. Audit big (BIGN) was found to be statistically significant and retained its significant level over the three year period. The audit modification report (MODIFIED) was significant at one year before failure in the logit model. Furthermore, the variable related to the three designated trustee companies (TRUSTEE) holds its significant level at t-2 and t-1 in the logit model. The Big 4 (BIGN) and audit modification (MODIFIED) as audit characteristics and TRUSTEE were significant in the hazard model. The overall results of Agency-related information confirmed the differences between failed and non-failed companies and the importance of audit and trustee characteristics in increasing the likelihood of failure. While non-financial variables can be used to predict failure, they are not sufficient and reliable enough on their own.

The last objective was examined the integration of both sets of variables. The integration of both groups of variables increases the model's predictive ability, both in the logit model and the hazard model. In short, the combined model performs better than the models built solely on financial or non-financial variables.

The overall accuracy of combined Models (3-1, 3-2 and 3-3) is more than 85%, with the highest accuracy of 89.70% at three years before failure in the logit model. Model 6 also provides the highest accuracy rate among the three hazard models. Furthermore, the lowest level of false negative and false positive proves the best performance of Model 3-3 and Model 6 in comparison with the other models in failure prediction. However, the AUC, Gini, KS and H statistics which measure the discriminant power of the models shows that Model 3-3 (which integrates both financial and non-financial variables), has the best discriminative power.

Overall, the results confirm that financial and non-financial information presented in the annual reports can be used to provide insight into the stability of individual finance companies and can be used to predict the risk of failure.

6.5 Limitations of the Study

As with all research projects, this study also suffers from a number of limitations. The first limitation of this study relates to the relatively small sample size. Data was limited to 35 failed financial companies over three consecutive years. Additionally, there were limited numbers of failed finance companies with available data for the test sample. Therefore, the results of classification accuracy and especially the discriminant power of out-of-sample cannot generate any significantly valid influence.

Secondly, this study focused only on failed New Zealand financial institutions. Therefore comparison with other jurisdictions should consider necessary justifications, taking into consideration the socio-economic environment.

6.6 Recommendations for Future Research

The findings of this study, together with the limitations, provide opportunities for future research. First and foremost, there is a need for more studies on the nature and structure of trusts, specifically the characteristics of the professional trustee and possible gaps in legislation related to the establishment of trusts, their responsibilities and activities. Additionally, it is recommended that future studies include other proxies for Agency-related variables and examine their impact on failure prediction. Furthermore, future research could examine the new regulation around NBDT prudential requirements for the potential gaps to prevent future related failure risks. Lastly, scholars should examine different machine learning models and compare their accuracy with other prediction models to test the robustness of the results. These findings will be beneficial in determining the best prediction models.

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Appendices

A.1 Summary of NBDT Prudential Requirements Currently in Force

Requirements	Summary	Timing of Requirements
Credit ratings	NBDTs are required to have a local currency (New Zealand dollar), long-term, issuer ratings, given by: - Standard and Poor's Rating Services; - Moody's Investors Service; or - Fitch Ratings.	In force since 1 March 2010.
Governance	NBDTs that are companies or building societies must have a chairperson who is not an employee of either the NBDT or a related party and must have at least two independent directors. NBDTs that are subsidiaries are prohibited from including provisions in their constitutions that would allow directors to act otherwise than in the best interests of the NBDT.	In force since 1 December 2010.
Risk Management	NBDTs are required to have a risk management programme that outlines how the NBDT identifies and manages its key risks. This programme is to be submitted to, and approved by, the NBDT's trustee.	In force since 1 September 2009.
Capital	A minimum capital ratio is required to be included in the NBDTs' trust deeds. This ratio must be at least 8% for NBDTs with a credit rating from an approved credit rating agency. For those without a credit rating from an approved rating agency, the minimum capital ratio specified in the trust deed must be at least 10%.	In force since 1 December 2010.
Related Party Exposure Limits	Related party restrictions place a limit on the aggregate credit exposures of an NBDT or the borrowing group; all related parties must be specified in NBDTs' trust deeds. The related party exposures should not exceed a maximum limit of 15% of tier one capital. The definition of "related parties" is expanded under the regulations.	In force since 1 December 2010.
Liquidity	Liquidity regulations require every NBDT and its trustee to ensure that the NBDT's trust deed include one or more quantitative liquidity requirements that are appropriate to the characteristics of the NBDT's business, and that take into account the liquidity of the NBDT and the liquidity of any borrowing group. The Reserve Bank has published guidelines for NBDTs and trustees to assist with the development of the quantitative liquidity requirements.	In force since 1 December 2010.
Suitability Assessment of	NBDTs must notify the Reserve Bank when a director or senior officer of the NBDT (or a person who it is proposed	In force since 1 May 2014

Certain Directors and Senior Officers	to appoint as a director or senior officer of that NBDT) raises one or more prescribed "suitability concerns". The Reserve Bank will then carry out a suitability assessment of that person. The person must cease to act in the role (or not be appointed to the role) where the Reserve Bank has declined to issue a notice of non-objection in respect of the person.	
Changes of Ownership	An application must be made to the Reserve Bank to approve a transaction that will result in a person: 1) having the direct or indirect ability to appoint 25% or more of an NBDT's governing body; or 2) having a qualifying interest in 20% or more of the voting securities issued by the NBDT. A transaction having this affect can only proceed with the Reserve Bank's approval.	In force since 1 May 2014

A.2 Codes in R to Calculate H, AUC, Gini, and KS

```
inp <- read.table(file.choose(), header = TRUE, sep = ";");
#   DAVID J. HAND, DEPARTMENT OF MATHEMATICS, IMPERIAL COLLEGE, LONDON #
d.j.hand@imperial.ac.uk
# This is R code for H, AUC, AUCH, GINI, and KS statistic
# In addition to these statistics, the output includes
# - the kernel smoothed score distributions of the two classes
# - the ROC curve and convex hull
#  - a plot of the minimum loss produced for each value of c
#  - the weight function implicitly used by the AUC, as a function of score
# - the weight function implicitly used by the AUC, as a function of c d


# data is in a matrix called �inp� with two columns
# column 1: classes, labelled 0 or 1
# column 2: classifier scores
n0n1 <- nrow(inp);
x <- t(inp);

# alpha and betad are the parameters in the beta  # cost distribution ~ c^alpha *
(1-c)^betad
alpha <- 2;
betad <- 2;
par(mfrow = c(3, 2));

# Smoothed histograms
class0 <- x[, x[1,] == 0];
class1 <- x[, x[1,] == 1];
xmin <- min(x[2,]);
xmax <- max(x[2,]);
plot(density(class0[2,]), xlim = c(xmin, xmax), main = "Kernel smoothed score
distributions ", xlab = "Score ");
lines(density(class1[2,]), lty = 4);

# order data into increasing scores
zord <- order(x[2,]);
sc <- x[, zord];
n1 <- sum(sc[1,]);
n0 <- n0n1 - n1;
pi0 <- n0 / n0n1;
pi1 <- n1 / n0n1;

# Calculate the raw ROC, replacing any tied # sequences by a �diagonal� in the ROC
curve.
# The raw ROC starts at F0[1]=0, F1[1]=0, and ends at # F0[K1]=n0, F1[K1]=n1.
F0 <- c(0:n0n1);
F1 <- c(0:n0n1);
sc <- cbind(sc, sc[, n0n1]);
K1 <- 1;
k <- 2;
for (i in 1:n0n1) {
    F0[k] <- F0[K1] + (1 - sc[1, i]);
    F1[k] <- F1[K1] + sc[1, i];
    K1 <- k;
    k <- if (sc[2, i + 1] == sc[2, i]) (k)
    else (k + 1);
    }
F0 <- F0[1:K1];
F1 <- F1[1:K1]
```

```
# Plot the ROC plot(F1/n1,F0/n0, xlab= "F1 ",ylab= "F0 ",type= "l", main= "ROC
curve and convex hull ") lines(c(0,1),c(0,1),type= "l")
# Compute KS statistic
KS <- max((F0 / n0) - (F1 / n1));
# Find the upper concave hull
G0 <- c(0:(K1 - 1));
G1 <- c(0:(K1 - 1));

i <- 1;
hc <- 1;
while (i < K1) {
    c1 <- c((i + 1):K1);
    for (j in (i + 1):K1) {
        u1 <- (F1[j] - F1[i]);
        u0 <- (F0[j] - F0[i]);
        c1[j] <- u1 / (u1 + u0);
    }
    argmin <- i + 1;
    c1min <- c1[i + 1];
    for (k in (i + 1):K1) {
        argmin <- if (c1[k] <= c1min)(k) else (argmin);
        c1min <- c1[argmin];
    }
    hc <- hc + 1;
    G0[hc] <- F0[argmin];
    G1[hc] <- F1[argmin];
    i <- argmin;
}

G0 <- G0[1:hc] / n0;
G1 <- G1[1:hc] / n1;

# Draw hull lines(G1,G0,type= "l",lty=2)
# Calculate the LHalpha value
cost <- c(1:(hc + 1));
b0 <- c(1:hc + 1);
b1 <- c(1:hc + 1);

cost[1] <- 0;
cost[hc + 1] <- 1;

b0[1] <- pbeta(cost[1], shape1 = (1 + alpha), shape2 = betad) * beta((1 + alpha),
betad) / beta(alpha, betad);
b1[1] <- pbeta(cost[1], shape1 = alpha, shape2 = (1 + betad)) * beta(alpha, (1 +
betad)) / beta(alpha, betad);
b0[hc + 1] <- pbeta(cost[hc + 1], shape1 = (1 + alpha), shape2 = betad) * beta((1 +
alpha), betad) / beta(alpha, betad);
b1[hc + 1] <- pbeta(cost[hc + 1], shape1 = alpha, shape2 = (1 + betad)) *
beta(alpha, (1 + betad)) / beta(alpha, betad);
for (i in 2:hc) {
    cost[i] <- pi1 * (G1[i] - G1[i - 1]) / (pi0 * (G0[i] - G0[i - 1]) + pi1 *
(G1[i] - G1[i - 1]));
    b0[i] <- pbeta(cost[i], shape1 = (1 + alpha), shape2 = betad) * beta((1 +
alpha), betad) / beta(alpha, betad);
    b1[i] <- pbeta(cost[i], shape1 = alpha, shape2 = (1 + betad)) * beta(alpha, (1
+ betad)) / beta(alpha, betad);
}


LHalpha <- 0;
for (i in 1:hc) {
```

```
    LHalpha <- LHalpha + pi0 * (1 - G0[i]) * (b0[(i + 1)] - b0[i]) + pi1 * G1[i] *
(b1[(i + 1)] - b1[i]);
}

B0 <- pbeta(pi1, shape1 = (1 + alpha), shape2 = betad) * beta((1 + alpha), betad) /
beta(alpha, betad);
B1 <- pbeta(1, shape1 = alpha, shape2 = (1 + betad)) * beta(alpha, (1 + betad)) /
beta(alpha, betad) -
    pbeta(pi1, shape1 = alpha, shape2 = (1 + betad)) * beta(alpha, (1 + betad)) /
beta(alpha, betad);
H <- 1 - LHalpha / (pi0 * B0 + pi1 * B1);


# Calculate the area under the ROC curve, AUC
K11 <- K1 + 1;
F0[K11] <- n0;
F1[K11] <- n1;
F0 <- F0[1:K11];
F1 <- F1[1:K11];
F0A <- F0[2:K11];
F0B <- F0[1:K1];
F1A <- F1[2:K11];
F1B <- F1[1:K1];
AUC <- sum((F0A - F0B) * (n1 - (F1A + F1B) / 2)) / (n0 * n1);
Gini <- 2 * AUC - 1;

# CALCULATE THE AREA UNDER THE CONVEX HULL, AUCH
AUCH <- 0;
for (i in 1:(hc - 1)) {
    AUCH <- AUCH + G0[i] * (G1[i + 1] - G1[i]) + 0.5 * (G0[i + 1] - G0[i]) * (G1[i
+ 1] - G1[i]);
}

# CALCULATE THE MINIMUM LOSS VS c CURVE
Q <- c(1:(hc + 1));
for (i in 1:hc) {
    Q[i] <- cost[i] * pi0 * (1 - G0[i]) + (1 - cost[i]) * pi1 * G1[i];
}
Q[(hc + 1)] <- 0;
plot(cost, Q, type = "l", main = "Minimum loss by cost ", xlab = "cost ", ylab =
"Minimum achievable loss ");

# PLOT THE AUC MIXTURE WEIGHT FUNCTION IN TERMS # OF THE SCORE
plot(density(x[2,]), lty = 1, xlab = "Score ", main = " AUC measure weight function
of T", ylab = "W(t)");
# PLOT THE AUC MIXTURE WEIGHT FUNCTION IN TERMS # OF THE COST
aucd <- c((n0 * G0 + n1 * G1), 1);
aucd2 <- c(1, (n0 * G0 + n1 * G1));
aucf <- (aucd - aucd2) / n0n1;
plot(cost[2:hc], aucf[2:hc], type = "h", xlim = c(0, 1), ylim = c(0, 1), main =
"AUC measure weight function of c", xlab = "Cost", ylab = "w(c)");
# PLOT THE BETA WEIGHT FUNCTION IN TERMS OF THE COST
b <- c(1:100) / 100;
y <- dbeta(b, alpha, betad);
plot(b, y, type = "l", xlab = "Cost ", main = "H measure weight function of c",
ylab = "w(c) ");

H;
AUC;
Gini;
AUCH;
KS;
```